MULTIOBJECTIVE DESIGN OPTIMIZATION OF GAS TURBINE BLADE WITH EMPHASIS ON INTERNAL COOLING

by

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ABSTRACT

In the design of mechanical components, numerical simulations and experimental methods are commonly used for design creation (or modification) and design optimization. However, a major challenge of using simulation and experimental methods is that they are time-consuming and often cost-prohibitive for the designer. In addition, the simultaneous interactions between aerodynamic, thermodynamic and mechanical integrity objectives for a particular component or set of components are difficult to accurately characterize, even with the existing simulation tools and experimental methods. The current research and practice of using numerical simulations and experimental methods do little to address the simultaneous "satisficing" of multiple and often conflicting design objectives that influence the performance and geometry of a component. This is particularly the case for gas turbine systems that involve a large number of complex components with complicated geometries.

Numerous experimental and numerical studies have demonstrated success in generating effective designs for mechanical components; however, their focus has been primarily on optimizing a single design objective based on a limited set of design variables and associated values. In this research, a multiobjective design optimization framework to solve a set of user-specified design objective functions for mechanical components is proposed. The framework integrates a numerical simulation and a nature-inspired optimization procedure that iteratively perturbs a set of design variables eventually converging to a set of tradeoff design solutions. In this research, a gas turbine engine system is used as the test application for the proposed framework. More specifically, the optimization of the gas turbine blade internal cooling channel configuration is performed. This test application is quite relevant as gas turbine engines serve a

critical role in the design of the next-generation power generation facilities around the world. Furthermore, turbine blades require better cooling techniques to increase their cooling effectiveness to cope with the increase in engine operating temperatures extending the useful life of the blades.

The performance of the proposed framework is evaluated via a computational study, where a set of common, real-world design objectives and a set of design variables that directly influence the set of objectives are considered. Specifically, three objectives are considered in this study: (1) cooling channel heat transfer coefficient, which measures the rate of heat transfer and the goal is to maximize this value; (2) cooling channel air pressure drop, where the goal is to minimize this value; and (3) cooling channel geometry, specifically the cooling channel cavity area, where the goal is to maximize this value. These objectives, which are conflicting, directly influence the cooling effectiveness of a gas turbine blade and the material usage in its design. The computational results show the proposed optimization framework is able to generate, evaluate and identify thousands of competitive tradeoff designs in a fraction of the time that it would take designers using the traditional simulation tools and experimental methods commonly used for mechanical component design generation. This is a significant step beyond the current research and applications of design optimization to gas turbine blades, specifically, and to mechanical components, in general.

To my beloved Father

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CHAPTER 1:
INTRODUCTION

1.1 Background

The increase in demand for energy and its resources have pushed the design of the turbine engine to its physical limits in order to achieve the highest possible efficiency. In 2008, the electric power generation industry generated revenue of about US$112 billion in the U.S. alone, which is a 12% increase in energy consumption compared to 2005, which generated revenue of US$100 billion (IBISWorld, 2008). It has been forecasted that over the next 25 years, the world's energy consumption will grow by 50%. This growth will, in turn, increase the world's dependence on electric power to meet its energy needs.

Electric power is expected to remain the fastest growing form of worldwide end-use energy through 2035, as it has been for several decades. At least one-half of the forecasted increase in worldwide energy consumption through 2035 will be attributed to electric power generation. Figure 1-1 shows that it has also been estimated that the worldwide net electricity generation will nearly double over next 25 years, from 19 trillion kilowatt-hours in 2008 to 35 trillion kilowatt-hours in 2035 (DOE, 2011). Figure 1-1 shows that the significant part of the growth in electricity generation is attributed to the countries that are not members of the Organization for Economic Cooperation and Development (OECD). The increase in demand for energy over the next three decades ultimately increases the use of all energy sources, as shown in Figure 1-2 except for liquid fuels, assuming that world oil prices remain relatively high throughout this period.

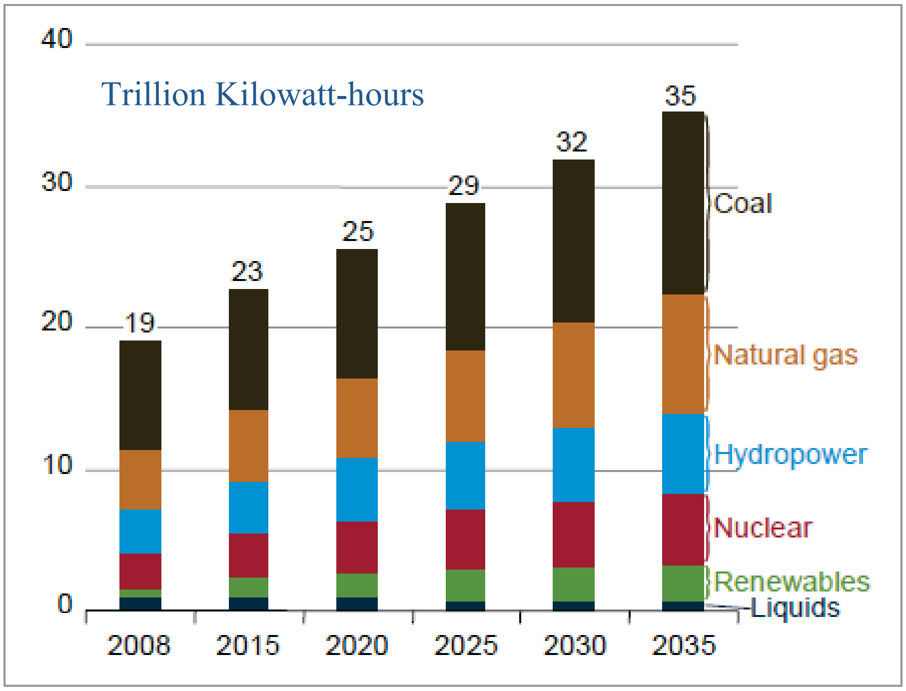


Figure 1-1: World net electricity generation during the period 2008-2035 (obtained from DOE-EIA, 2011)

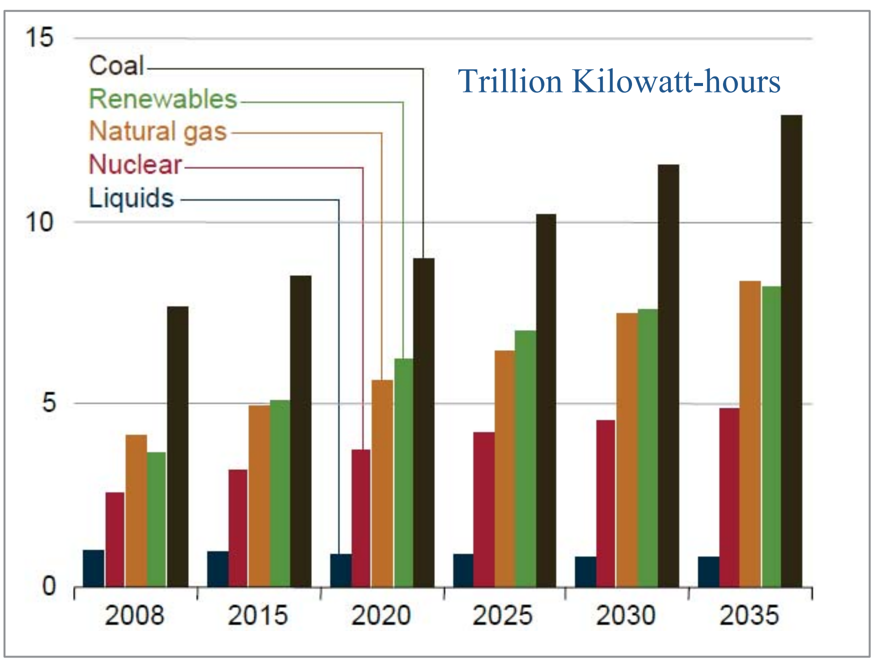


Figure 1-2: World electricity generation by fuel type during the 2008-2035 (obtained from DOE-EIA, 2011)

From Figure 1-2 it can be noticed that coal has continued to be a major source of fuel for electricity generation, although nuclear power generation increased at a rapid pace from the 1970s through the 1980s, and natural gas fired generation grew rapidly in the 1980s and 1990s. The U.S. true measure of energy strength is coal. It is estimated by the Department of Energy (DOE) that one-fourth of the global coal reserves are found in the United States. The energy capability of the U.S. coal resources exceeds that of the entire world's known recoverable oil. The Clean Coal Technology & the Clean Coal Power Initiative across America describes a new generation of energy processes that sharply reduce atmospheric emissions and other pollutants from coal-burning power plants (DOE, 2002). The new energy process is the adaptation of advanced gas turbine technologies to use with coal-burning power plants. This has been successfully used at Tampa Electric's Polk Station and the Wabash River Repowering projects under the Clean Coal Technology Initiative (DOE, 2003).

1.2 The Role of Turbines in Power Generation

Turbines have been considered energy workhorses for generations. Regardless of the type of fuel used, turbines are at the heart of almost all of the world's electricity generating systems. The increasing trend in world energy consumption (see Figure 1-1) has caused a considerable increase in large-scale electric power generation, which largely depends on the use of turbines. Gas turbines are key complex engines of advanced systems designed for new electric power plants in the United States and around the world. It is estimated that turbines are involved in the generation of more than 95% of all electricity added to the U.S. power grid. Furthermore, almost all of the world's electricity that is sent to the major power grids is generated by turbines (EIA-

DOE, 2009). From gas turbines and steam turbines used at coal-burning power plants to water turbines used at hydro-electric power plants, turbines are used in a number of applications. Figure 1-3 shows the general categories of turbines based on the working fluid (i.e., steam, gas, water or wind) used to power them. Among the different types of turbines, gas turbines are more commonly used due to their high thermal efficiency, relatively low-cost energy, versatility (i.e., multi-fuel capability), and size. Furthermore, gas turbine engines are being used in an increasing number of industrial settings. For instance, gas turbines are used in aircraft propulsion, marine propulsion, and land-based power generation. The increased need for energy around the world has also increased the need for the construction of additional land-based power generation facilities. In 2008, 1054 units of gas turbines are ordered by power plants, a 15% increase over the previous year's 916 units (D&GTW, 2008). In 2008, the turbine product segment account for US$12 billion, which is 20.7% of industry revenue in the U.S. alone. It is also estimated that the turbine product segment's share of industry revenue will increase by 5% through the year 2014 due to increased demand for electricity and the refurbishment of outdated power stations in developing economies with cleaner burning gas turbines (IBISWorld, 2009).

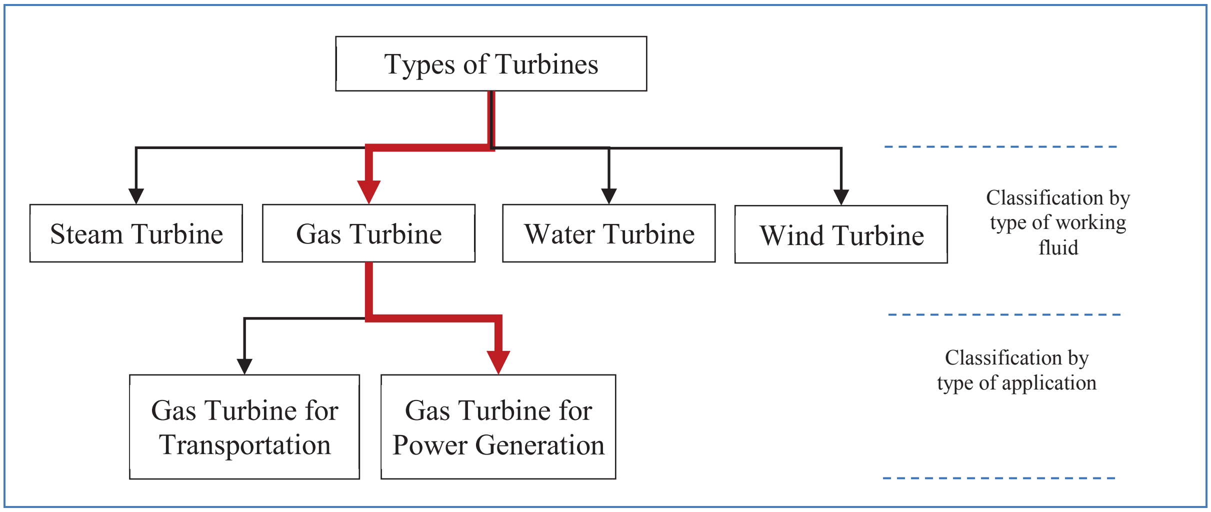


Figure 1-3: Classes of turbines by working fluid

Gas turbines do, however, possess major, albeit common, limitations. The conditions of the operating environment of the gas turbine greatly affect the engine reliability. Typically, gas turbines operate at high temperatures that often range from 2500º F to 3500º F. In addition, unpredictable pressure variation occurs due to the internal combustion within the engine, and this pressure can vary (depending on load) from as low as 40.5 psi to as high as 45 psi (Boyce, 2006). Finally, the centrifugal force on a single turbine blade could be up to several tons (Moustapha et al., 2003).

The failure of critical internal components in one or more engines in a gas turbine power plant can cause severe economic loss for both the producer as well as the consumer of electricity due to the power outage caused by gas turbine failure. The diversity in electric power usage by the commercial, industrial and residential sectors makes it difficult to estimate the actual economic impact caused by power outages. One attempt to quantify the economic impact is reported by LaCommare and Eto (2004). In their study at the University of California Berkley, the initial base case estimate of the annual economic loss due to power interruptions to U.S.

electricity consumers is US$79 billion. Their analysis of uncertainty suggests that the economic loss could range anywhere between US$22 billion to as high as US$135 billion (LaCommare and Eto, 2004). Even though the major contributor of power outage is attributed to transmission grid failure, power outage due to gas turbine failure cannot be neglected. Thus, a modest increase in the reliability of gas turbines can reduce significant economic loss.

The growing demand for electricity has motivated personnel at the world's power generation facilities to look for more reliable, efficient and higher power advanced gas turbine systems than ever before. Achieving high reliability and thermal efficiency of gas turbines is of continuing engineering concern due to the harshness of the turbine operating conditions. In fact, it is these operating conditions of gas turbines that motivate engineers and researchers to study gas turbines to increase their core power output and improve their efficiency and reliability. In this research investigation, the area of focus is gas turbines and gas turbine engine reliability.

1.3 The Working Principle of Gas Turbine Engines

The simplest and most common gas turbine is an in-line axial flow turbine, as shown in Figure 1-4, where the mechanical arrangement of all its components are linear and aligned with the air and combusted gas fluid flow through the engine. The engine operates by guiding incoming air flow into the compressor, which in turn, compresses and delivers highly-pressurized air into the combustor section of the engine. This is the mainstream flow. The combustor burns the injected fuel using the compressed air delivered from the compressor. The mainstream flow (or, hot gas) is a combustion mix of air, fuel and unburned hydrocarbons, and it can reach temperatures as high as 3000º F and can produce high pressure variations (Boyce, 2006;

Moustapha et al., 2003; Han et al., 2000). The hot gas enters a series of turbine stages, where a stage is composed of a set of vanes and a set of turbine blades. The hot gas expands towards atmospheric (or, ambient) pressure in each stage, and this gas expansion runs the turbine to generate output shaft power. This shaft power is used to drive the compressor, and it is also used to power the generator. The hot gas path components are cooled by a percentage of the compressed air (i.e., a secondary air flow) that is extracted by a cooling supply system from the compressor (indicated by the dotted arrows in Figure 1-4). This secondary air flow is often referred to as the coolant, and this term is used throughout the remainder of this document when referring to this cooling air flow.

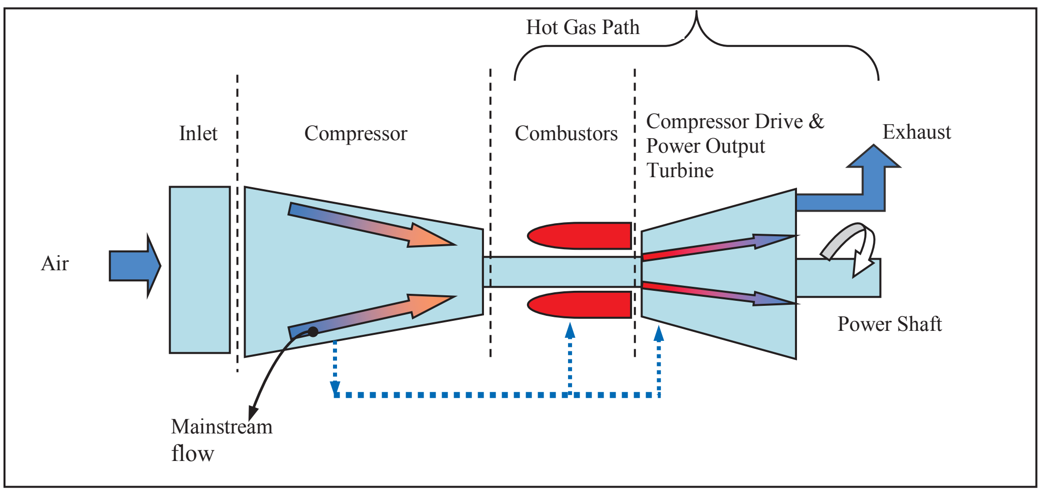


Figure 1-4: In-line axial gas turbine mechanical component arrangement

Figure 1-5, an artistic cutaway view, provides a more detailed perspective of the in-line axial gas turbine. The figure shows the compressor housing, which has eight stages, where each stage contains a set of stator blades and a set of compressor blades (or rotor blades). It is important to note that the number of stages in the compressor greatly depends on the pressure ratio required for the power generation application. The stator blades guide incoming air at a particular angle, and then the compressor blades compress and deliver the air to the next stage for further compression. Next, in Figure 1-5, the turbine housing has three stages, and each stage consists of a set of vanes and a set of blades. Again, the number of stages in the turbine greatly depends on the desired pressure ratio for the power generation application. The hot gas from the combustor exits is directed to the turbine housing, as shown in Figure 1-5. The temperature at which the hot gas enters the first stage of the turbine is called the turbine rotor inlet temperature, or turbine inlet temperature (TIT). The row of vanes guides the incoming hot gas at a particular angle onto the row of rotor blades, and the blades rotate as the hot gas expands. This expansion continues in Stages 2 and 3 of the turbine before the hot gas is expelled as exhaust.

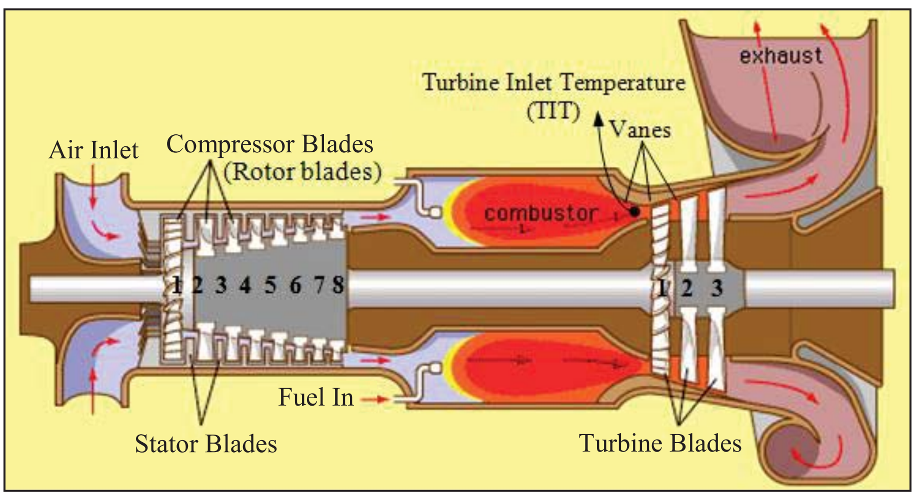


Figure 1-5: Cutaway view of typical gas turbine engine (obtained from Britannica Encyclopedia, 1999)

1.3.1 The Turbine Inlet Temperature

The turbine engine parameter of greatest influence on core power and thermal efficiency is the TIT. To meet the demand requirements of power plants, such as increased thermal efficiency and increased power output, the owners of the gas turbines operate them at high inlet temperatures. At present, the more advanced gas turbine engine systems operate at temperatures of 2200º F to 2700º F, which is above the permissible metal temperatures (Han (2004). The historic increase in TIT, as shown in Figure 1-6, is a result of an attempt by gas turbine manufacturers to simultaneously increase the thermal efficiency and the specific core power per unit mass of air flow. The ideal Brayton Cycle curve, which is the performance theoretically obtainable with ideal components throughout the gas turbine engine, indicates a steady increase in specific core power until the Hydrocarbon Stoichiometric Limit is reached, which is the maximum temperature limit attained by burning fuel 100%. All existing gas turbine engine systems fall below this ideal curve. However, they follow the same general trend as this curve, from the very first gas turbine engines designed by Von Ohain (1939) and Whittle (1937) to more recent developments. Over this time span, there has been a several-fold increase in efficiency. However, there have also been very large increases in turbine inlet temperature.

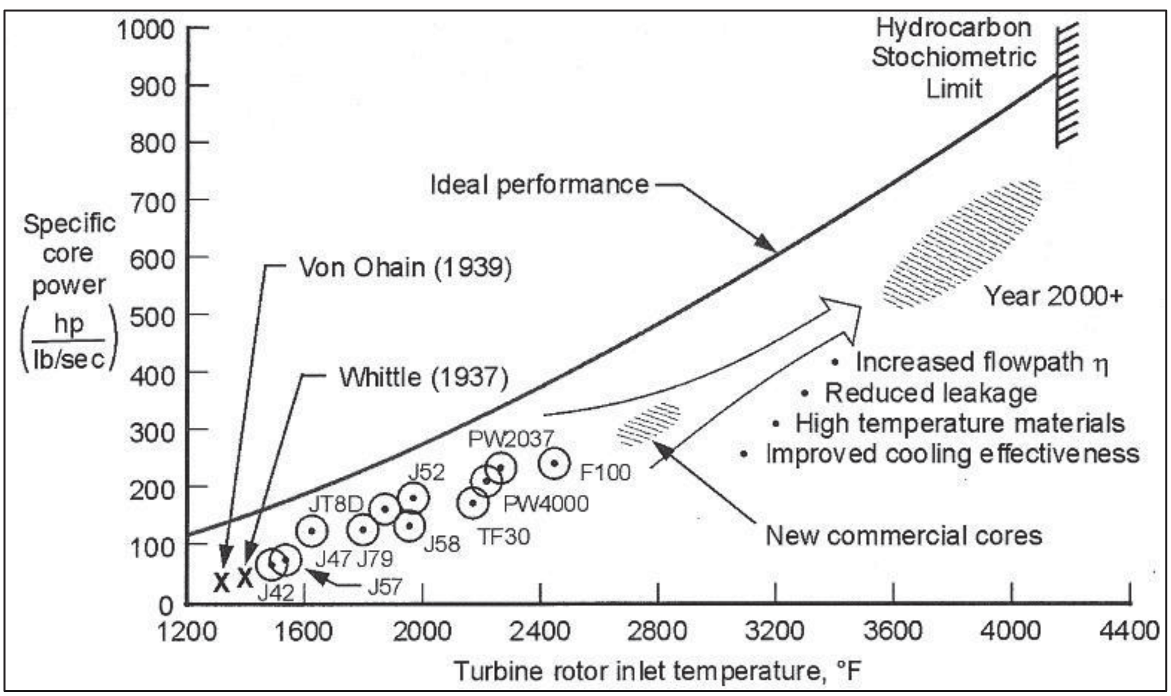


Figure 1-6: Historical trend of improving the core performance by increasing turbine rotor inlet temperature (Koff, 1991; Reprinted with permission of the AIAA)

Increasing the TIT is the primary contributor to creating the harsh operating environment for these critical components, in particular the turbine blade. For instance, increasing the turbine inlet temperature increases the amount of heat transferred to the blades. In addition to increasing the pressure on the blades, extreme inlet temperatures can also destroy the ceramic thermal barrier coating that protects the blades, which invariably reduces their useful life. The three most common failure mechanisms that contribute to the useful life of blades due to high temperatures are creep, thermal fatigue and corrosion. These types of failure mechanisms not only depend on blade design and the type of fuel consumed by the engine, but it also depends on the duration of operation of the engine and the environment in which the engine operates.

It is fundamentally necessary that gas turbines operate in high temperatures and uncertain combustion flow conditions in order to meet the increasing demand of energy. The turbine blade is one of the critical components, among many other components, that needs cooling. The advances in the turbine cooling and material technology have enabled the life of the blade to be increased in spite of higher turbine inlet temperatures. One of the most important parameters for measuring and assessing the cooling performance of a blade is the cooling effectiveness ϕ,

$$\phi = \frac{T_g - T_m}{T_g - T_c}, \tag{1.1}$$

where T_c, T_g and T_m refer to the coolant temperature, gas temperature and metal temperature, respectively. If $\phi = 0$, then it represents no cooling effect, and $\phi = 1$ is the case of perfect cooling, where the blade metal temperature and coolant temperature are equal. The cooling effectiveness is influenced by many variables such as the blade design, arrangement of cooling channels, design configuration of turbulators (e.g., ribs, pin-fins, etc.) inside the cooling channels and the way in which the coolant is ejected from the blade. More importantly, it is influenced by the mass flow rate of cooling air used.

1.4 Internal Cooling of a Gas Turbine Blade

The design of a blade and its cooling supply system vary across gas turbine engine manufacturers. However, in general, the developments in gas turbine blade cooling are shown in Figure 1-7. In the figure, the inlet temperature is plotted against blade cooling effectiveness ϕ. Turbine blade materials typically melt at a temperature of about 2400º F (Moustapha et al., 2003; Han et al., 2000). A solid blade with no internal cooling has a cooling effectiveness $\phi = 0$ and is limited to temperatures that are, by current standards, low (i.e., less than 1800º F). In order to achieve higher inlet temperatures, the turbine blades must be cooled. One type of blade design is convection (i.e., heat transfer from a solid material to a fluid media). In this kind of blade, the coolant passes through a series of holes in the blade, so that cooling is achieved by heat transfer from the blade material to the cooling air flow. The cooling effectiveness ϕ of a simple blade cooled by convection alone is approximately 0.40 for a moderate TIT of 2200º F (see Figure 1-7). Another type of blade design is film/convection cooled blades. In this type of blade design, the cooling air passes through the blade internal cooling channels. Then, the coolant passes through holes or slots to the outer surface of the blade forming cooling films. These films act as an insulating blanket of coolant that limits heat transfer from the mainstream flow (hot gas) to the blade surface (Moustapha et al., 2003; Han et al., 2000). Film cooled blades produce a cooling effectiveness ϕ of about 0.60, resulting in an inlet temperature of about 3000º F (see Figure 1-7). Therefore, an increase in cooling effectiveness allows gas turbine operators to increase TIT, which, in turn, increases the thermal efficiency of the system without compromising the life of the blade.

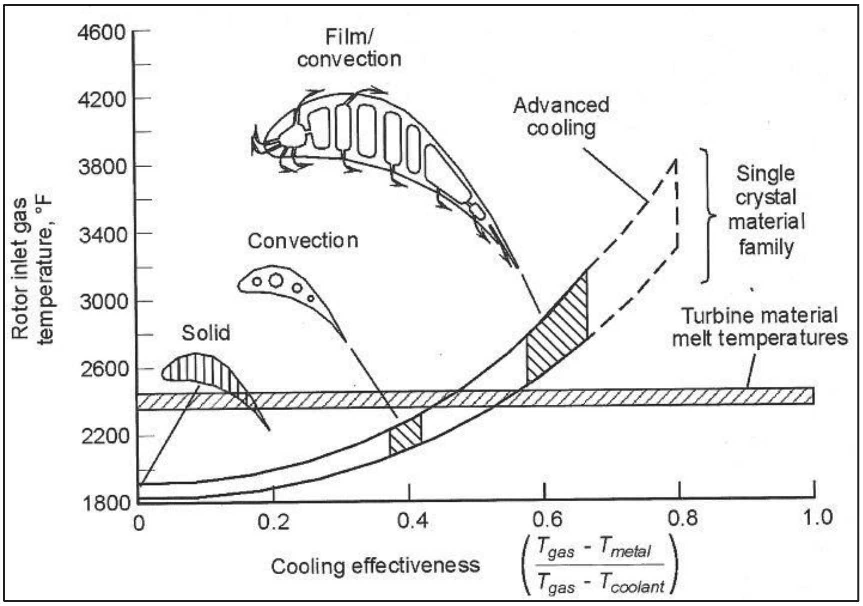


Figure 1-7: Improving performance with improved turbine blade cooling Techniques and materials (Koff, 1991; Reprinted with permission of the AIAA).

Figure 1-8 shows several cooling techniques that are commonly used in turbine blade design. There are three important cooling zones of a blade. Film cooling takes place in the leading edge (Zone 1), the pressure and suction surfaces on the blade (Zone 2) and the blade tip region (Zone 3). The leading edge is also cooled by impingement cooling at the inner wall. The center of the blade is cooled by the internal rib-roughened cooling channels. The rib-roughened cooling channels cause turbulence in the coolant flow as the air passes over and around the ribs. The turbulent air removes a fraction of the heat conducted by Zone 2 from the blade (see Figure 1-8). The same cooling air exits through the cooling holes in Zones 1, 2 and 3 forming a thin, cool, insulating blanket along the external surface of the turbine blade. The trailing edge of the blade is cooled by pin fins with trailing edge injection of coolant. Film cooling effectiveness depends on two parameters the mass flow rate and flow velocity of the coolant, which in turn depends on the rib configuration in the internal cooling channels. Therefore, it is important to study the internal cooling channel ribs configuration to cool all zones efficiently.

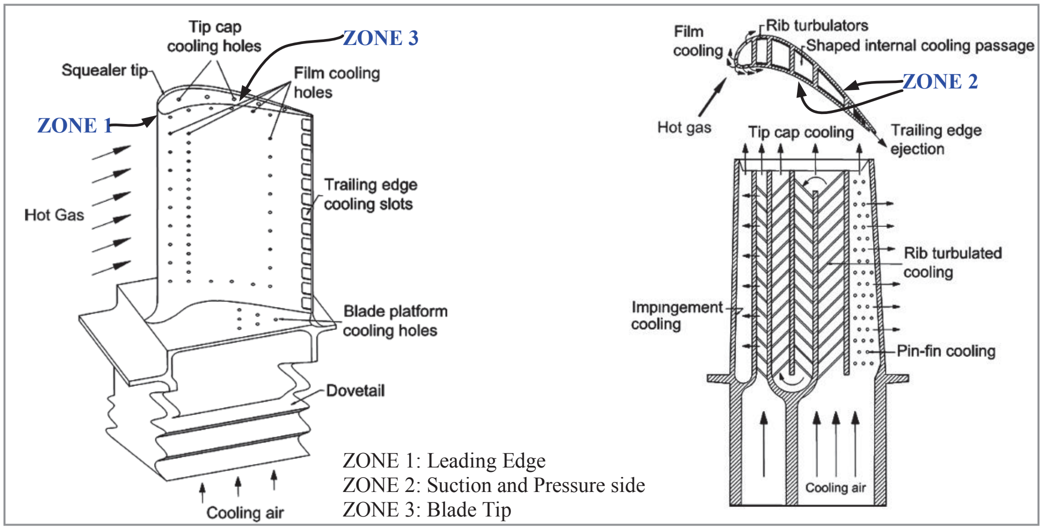


Figure 1-8: The schematic of a modern gas turbine blade with common cooling techniques (Han, 2004; Reprinted with permission of the Taylor & Francis Group).

The most influencing factor on cooling effectiveness ϕ is the mass flow rate ($\dot{m}$) of the coolant, and this rate is usually measured as a percentage of the mainstream flow. Figure 1-9 shows that ϕ increases rapidly with a small percentage of coolant, but then the growth of the ϕ slows. To increase further cooling, a large amount of cooling air and/or different cooling techniques must be used. For example, for an engine of modest turbine inlet temperature, where only the first stage (i.e., a single row of vanes and blades) of the turbine engine needs cooling, and the total turbine cooling air flow may be only 4% to 5% of the mainstream air flow. However, for a state-of-the-art engine where there are several stages and each stage has a row of turbine vanes and blades and these vanes and blades must be cooled, the percentage of total turbine cooling air flow can be as high as 25% to 30% of the mainstream air flow. Since the cooling air is drawn from the compressor at different stages, it represents a direct loss of engine efficiency due to a reduced amount of mainstream flow. Approximately 1% of coolant is a loss of approximately 1% of specific core power output (Logan, 1995; Moustapha et al., 2003). Therefore, it is important to balance the cooling air flow and mainstream air flow. This research investigation focuses on optimizing the design configuration of the internal cooling channel of a turbine blade in order to enhance the cooling so that the desired cooling effectiveness is achieved.

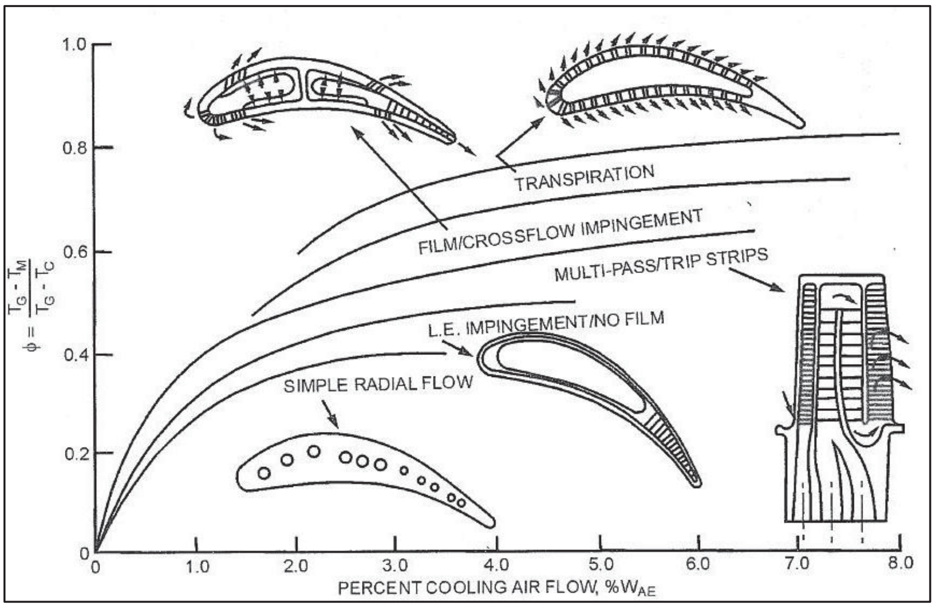


Figure 1-9: Effectiveness of different blade cooling techniques as a function of cooling air flow (obtained from Moustapha et al., 2003).

Considering the examples of various cooling schemes shown in Figure 1-9, the lowest cooling effectiveness and TIT of about 2100º F is obtained by a simple radial hole cooling design configuration. The combination of more advanced design configurations such as multi-pass, film/crossflow impingement and transpiration cooling achieve higher cooling effectiveness and inlet temperatures up to 2500º F for power plant turbines and up to 2800º F for advanced aircraft engines with the same percentage of coolant (Moustapha et al., 2003; Logan, 1995). Despite the recent developments in internal cooling technology, it is difficult to cool the blades significantly beyond an average cooling effectiveness ϕ = 0.50 (see Figure 1-9). Thus, there is a need to explore further internal cooling channel configurations, which directly impact a blade's cooling effectiveness.

1.5 Challenges of Gas Turbine Blade Cooling Channel Design

In general, the relationship among most of the critical components and internal subsystems in gas turbines are complicated, and the performance objectives of the turbine engine sometimes conflict. For example, the efficiency of gas turbines increases as TIT increases. However, operating at high temperatures decreases the life of the gas turbine and increases the operating costs of power plants. These conflicting objectives necessitate decisions that must consider tradeoffs between the objectives.

The optimization of the design configuration of the blade internal channel appropriately fits a multiobjective design optimization problem. It should satisfy two conflicting objectives: (1) maximize the cooling effectiveness to increase the blade life and reliability of the engine, and (2) minimize the pressure drop in the cooling channel. The minimization of the pressure drop is important in that, enough pressure must be retained in the cooling channel for satisfactory ejection of the coolant flow. If there is insufficient pressure in the cooling air flow, the exit velocity of the coolant will be lower than that of the mainstream air flow, and it will disturb the mainstream flow. This disturbance is called mixing loss and could contribute to the loss of efficiency. Thus, minimization of pressure drop inside the cooling channel is an important objective for designers to consider.

Due to the complex nature of the flow and heat transfer phenomena involved in cooling channel design, only few attempts have been made in applying multiobjective optimization techniques to the design of internal turbine blade cooling channels. The limited studies consider only two objective functions and convert the two objectives to a single composite objective function. However, no existing research simultaneously considers two or more objectives equally weighting the objectives.

1.6 Research Objectives

The aim of this research investigation is to apply multiobjective optimization techniques in engineering design. As explained in Section 1.3, this research specifically focuses on the feasibility study of multiobjective optimization of the gas turbine blade internal cooling channel to increase the useful life of the blade. The main goal of this investigation is to build a framework where multiobjective optimization is employed in order to accelerate and improve the design of blade internal cooling channels to enhance the heat transfer rate and the blade operating life. The specific objectives of this investigation are as follows:

Objective 1: Design a multiobjective procedure for the heat transfer optimization problem. The procedure is designed to rapidly converge to the true Pareto optimal front. In addition, the procedure generates a diverse set of Pareto optima so that they are evenly distributed along the front. Only with a diverse set of solutions can it be assured of having a viable set of tradeoff solutions among objectives.

Objective 2: Integrate commercially available numerical simulation software used to build computational fluid dynamics (CFD) model for the analysis of the flow field and associated heat transfer of different design configurations of cooling channel to optimization algorithm such as multiobjective evolutionary algorithms (MOEAs).

Objective 3: Automate the design optimization framework, i.e., the system should deliver a set of Pareto optimal solutions in one execution with minimal input data.

1.7 Expected Contributions of This Research Investigation

This investigation should contribute quite significantly to the body of knowledge of and advance the state-of-the-art in mechanical component design optimization. Gas turbines are the test application in which to implement and validate our research as gas turbines are complex in design and play a central role in global energy needs. This research potentially improves the design approach of gas turbine blades and the inherent cooling effectiveness and, in turn, improving the reliability, availability and maintainability of gas turbine engines.

1.8 Organization of This Document

The remainder of this document is organized as follows. CHAPTER 2 provides a brief summary of the related literature including the gas turbine blade cooling design and multiobjective optimization. CHAPTER 3 gives a brief overview of heat transfer concepts and fluid flow simulation. The chapter begins with definitions of different modes of heat transfer, fluid dynamics, and concludes presenting the governing equations that characterize heat transfer and fluid flow. Readers familiar with heat transfer and fluid mechanics can proceed directly to CHAPTER 4 without the loss of continuity. CHAPTER 4 provides an overview of multiobjective optimization and multiobjective optimization methods and discusses evolutionary algorithms as a multiobjective optimization procedure. Those who are familiar with multiobjective optimization in general and evolutionary algorithms as multiobjective optimization procedures specifically can proceed to CHAPTER 5

CHAPTER 5 describes the proposed optimization framework for solving multiobjective mechanical component design problems. The chapter provides a detailed description of the architecture of the proposed framework. The framework comprises two components – an Optimizer component and a Simulator component. The Optimizer component intelligently and iteratively perturbs the values of a set of design variables to create candidate design solutions. The Simulator component, which utilizes computational fluid dynamics, evaluates the candidate solutions to evaluate the quality of the designs.

The proposed optimization framework is systematically tested within a structured experimental framework in a computational study. CHAPTER 6 discusses the test application for the optimization framework, the set of design objectives and the set of design variables. In addition, the parameter settings for both Simulator and Optimizer are determined via pilot study.

The performance of the proposed optimization framework is assessed in CHAPTER 7 for one design objective and then for two design objectives, respectively. CHAPTER 8 then assesses the performance of framework under three design objectives. This document is concluded in CHAPTER 9 with a summary of the accomplishments and future steps in this research.

CHAPTER 2:
REVIEW OF PREVIOUS RELATED LITERATURE

2.1 Introduction

Engineering design is an iterative and often tedious manual task. The design iterations are carried out manually until satisfactory results are obtained. In this context, one can say any engineering design problem is an optimization problem. Formal optimization schemes are being used as part of the modern design process to achieve optimal designs of engineered system as well as components. While formal optimization methods are not fully integrated into all engineering design processes, their inherent ability and adaptability of these methods have assisted in developing robust designs. In this chapter, a review of the existing work in engineering design optimization is given.

2.2 Conventional Optimization Techniques in Engineering Design

The traditional approaches to engineering design optimization are experimental methods and numerical optimization methods. Experimental methods usually require the investigation of numerous variations about some nominal design. On the other hand, one is forced to experiment either on the real-world engineered system or on a scaled down model of the system if the functional relation between the design variables and the objective function is unknown. For the purpose of experimental optimization, one must be as flexible as possible to vary the independent design variables and have access to measuring instruments with which the dependent variables can be evaluated. Systematic investigation of all possible states of the system is costly if there are many design variables, and random sampling of various combinations is impractical for achieving the desired result (Schwefel, 1981). For example, in the design of an aircraft wing or wing-fuselage combination, numerous wind tunnel tests may be conducted, modifying the configuration only slightly between tests. The main purpose is to find the optimal geometric shape that maximizes important performance parameters. The modification of an aircraft wing or wing-fuselage for each experimental test is costly and fairly time-consuming. This suggests that use of less expensive numerical optimization methods for determining the best shape for the specified flight envelope (i.e., capabilities of an aircraft design in terms of speed and altitude) is more appropriate. Thus, the addition of a numerical approach in the design process reduces the amount of experimental effort and its associated cost to a great extent, and yet the all-important experimental verification of design is also retained (Vanderplaats, 1984). Scores of experimental approaches to gas turbine blade cooling have been studied. A review of these studies can be found in Han et al. (2000).

Numerical simulation optimization methods use high speed computers and information technology to help design engineers in tasks such as design, analysis, simulation and optimization. There are several commercially-available computer-aided engineering (CAE) software tools to perform these activities, and these tools are used in various stages of design to simulate, validate and optimize design parameters. CAE application areas include:

- Stress and strain analysis on mechanical components using finite element analysis (FEA);
- Thermal and fluid flow analysis using computational fluid dynamics (CFD);
- Mechanical event simulation (MES); and
- Tools for process simulation for operations such as casting, molding, and die press forming.

Thermal and flow analysis using CFD is a computer simulation that is used in the optimization of gas turbine blade cooling design. Application of CFD techniques to optimize gas turbine blade internal cooling alone has attracted many researchers in recent years (e.g., Chen et al., 2000; Jang and Han, 2001; Al-Qahtani et al., 2002; Saha and Acharya, 2004; Kim and Lee, 2007a; Xie et al., 2009; Iacovides and Launder, 2007). Apart from gas turbine design applications, many industrial design activities use CAE tools to obtain few design solutions by changing design variables manually. The optimization is achieved by comparing only a few design candidates and accepting the best design solution relative to some design objective. This approach is time-consuming and often never guarantees an optimal design solution. On the contrary, CAE tools are integrated with optimization algorithms so that they iteratively evaluate candidate designs in order to identify the best solution.

The experimental and numerical optimization method using computer simulation ignores the stochastic nature of design variables. This is mainly because the traditional deterministic design calculations use nominal (average) values of random variables and apply safety factors to simulate worst-case scenarios in an attempt to account for uncertainties caused by stochastic input variables. If the design of a system is complex where safety factors are generously applied due to the high risk involved, then these safety factors compound to cause over-design often with unknown system reliability. In some important cases, where there is an upper and lower specification or a functional limit exists, the safety factor method cannot be used, and a probabilistic design method (PDM) is used. PDMs use probability distributions of the design variables, instead of nominal values, in the design calculations. By using the probability distributions of the design variables, an engineer can design for a specific reliability or specification conformance by producing designs that are fairly robust to variations and, hence, can maximize safety, quality and economy.

There are many probabilistic analysis methods in use, some of the commonly used methods are: i) the First-Order Reliability Method (FRM), ii) the Second-Order Reliability Method (SRM), iii) the Fast Probability Integration (FPI), iv) the Response Surface Method (RSM), and v) the Monte Carlo Simulation (MCS). The application of PDMs in design first received attention in space exploration industry more than two decades ago. The deterministic approach favors the use of a factor of safety in launch vehicles to account for uncertainties, which not only leads to unknown reliability, but also often results in a substantial weight increase. It is estimated that the cost of delivering one pound of payload to low-earth orbit is about US$8,500 (McCurdy, 2001). Considering the cost associated with the weight of payload and risk involved in exploring space, NASA uses probabilistic design techniques to decrease the liftoff weight of launch vehicles drastically without compromising system safety and reliability. (Chamis, 1987; Shiao et al., 1988; Shiao and Chamis, 1994; Chamis, 2007).

Design engineers from other fields also apply PDMs in their designs concurrently. The catastrophic accidents of airlines, such as the incident in Sioux City, Iowa in 1989 due to an inherent material anomaly and the incident in Pensacola, Florida in 1996 due to an induced material anomaly, prompted a surge in the application of probabilistic design methods to commercial airlines gas turbine engine design (Enright et al., 2005).

2.3 Reliability-based and Probabilistic Design Methods for Gas Turbine Blade Design

Although probabilistic design methods are well-known and have been studied for many years, the application of PDMs to gas turbine blade design started gaining momentum only within the last decade. For example, Mucke (2000) introduce probabilistic approaches to design of cooled gas turbine blades. He uses Monte Carlo Simulation to predict the life of turbine blades. He treats the design variables as stochastic in nature and assumes a Gaussian distribution to obtain probability distribution of failure criteria and sensitivity of stochastic variables. In another similar study, Voigt et al. (2004) study the stochastic nature of material data, thermal loading and manufacturing tolerances on low cycle fatigue (LCF) life of the blade. The study by Sidwell and Darmofal (2005) evaluates the impact of blade-to-blade variability in cooling flow on the oxidation life of blade.

The probabilistic design methods discussed so far are linked primarily to reliability-based design tools. They are used to predict the useful life or reliability of a component based on the stochastic nature of its design variables. There are few drawbacks in integrating probabilistic design methods in design optimization. Firstly, it is often difficult to characterize the most appropriate probability distribution for each design variable due to the difficulty in obtaining data. Secondly, the objective of these methods is to predict the reliability of the component for a given level of variability in the design variables. However, probabilistic design methods fail to handle multiple objectives in design optimization.

2.4 Overview of Engineering Design Optimization Methods

There is a wide array of procedures that have been used for combinatorial optimization. These optimization procedures are becoming more and more popular in engineering design activities mainly because of the increased availability of more affordable high-speed computers. They are extensively used in engineering design problems where the focus is minimizing or maximizing a particular objective or set of objectives. These procedures are capable of addressing design optimization problems in many different and diverse disciplines unlike empirical methods that have been used in the recent past. For example, the recent advances made in the area of aerospace systems design and turbomachinery design is attributed to the development of accurate flow solvers and efficient optimization algorithms (Logan, 1995). Several optimization procedures addressing various engineering design problems have been developed over the years, and these methods can be broadly classified as gradient-based and non-gradient-based methods, as shown in Figure 2-1.

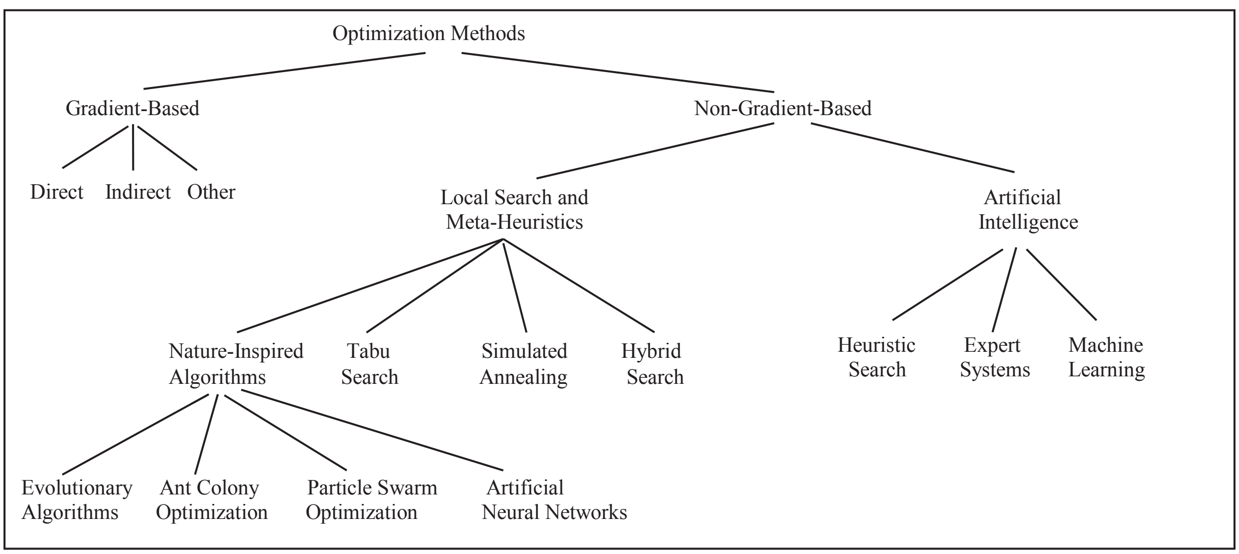


Figure 2-1: Overview of optimization procedures for engineering design problems

2.4.1 Gradient-Based Optimization Methods

The gradient-based optimization methods can be subdivided into two main classes: direct and indirect. Direct gradient methods converge iteratively to the local optimum of an objective function by moving in the direction relative to the local gradient. Indirect methods compute the local maxima by solving the usually nonlinear equations resulting from equating the gradient of the objective function equal to zero. This method is comparatively efficient in searching for optima. However, both direct and indirect methods are local in scope; they seek the best solution in the surrounding search region of the current point. Gradient-based search techniques have been widely used in many engineering optimization problems including aerodynamic shape optimization (Obayashi and Tsukahara, 1997; Catalano et al., 2008), and gas turbine design (Burguburu and le Pape, 2003; Kämmerer et al., 2004). However, the objective function in shape optimization usually falls under multimodal, and thus the optimum reached may be in the neighborhood of the initial design point. To find the global optimum, one must start the optimization iteratively from initial design points and check for correctness of the computed optima at each iteration. Existing turbine blade cooling optimization research focuses more on non-gradient-based methods.

2.4.2 Non-Gradient-Based Optimization Methods

Non-gradient-based approaches to design optimization are relatively new compared to gradient methods. This is mainly due to previous limited availability of high-speed computing. Figure 2-1 shows further classification of non-gradient-based methods.

2.4.2.1 Local Search and Meta-Heuristics

Design optimization problems can be characterized as a local search for the optimal solution over the space of all feasible design solutions. A special class of local search heuristics is called meta-heuristics. Meta-heuristics are a class of approximate methods that are capable of solving hard combinatorial optimization problems where classical heuristics have failed to be effective and efficient (Osman and Kelly, 1996). Meta-heuristic approaches have drawn significant attention from researchers and design engineers in the last decade. The main reason for their popularity in design optimization is that these approaches are likely to find global optimal solution without getting trapped at local optima as other approaches such as gradient methods. Another advantage of these methods is that they do not require any derivatives of the objective function in order to calculate the optimum (Shahpar, 2000).

The most popular meta-heuristics that are used for design optimization are nature-inspired procedures that include simulated annealing, evolutionary algorithms, tabu search, and ant colony optimization (see Figure 2-1). A number of researchers provide extensive reviews of these heuristics and discuss their applicability to general combinatorial optimization problems (e.g., Reeves, 1993; Rayward Smith, 1996; Glover and Laguna, 1997; Pham and Karaboga, 2000; Alidaee and Rego, 2005). These algorithms have all been successfully used in blade design optimization problems: simulated annealing (e.g., Ghaly and Mengistu, 2003; Tiow et al., 2002), tabu search (e.g., Kipouros et al., 2005), evolutionary algorithms (e.g., Muller and Walther, 2001; Foli et al., 2006; Li and Kim, 2008; Gosselin et al., 2009), ant colony optimization (e.g., Fainekos and Giannakoglou, 2003) and hybrid techniques (e.g., Burguburu and le Pape, 2003; Shahpar, 2000; Dumas et al., 2009). Specifically, evolutionary algorithms have been used extensively in the blade design optimization. These algorithms are nature-inspired heuristics based on the Darwinian evolution theory on survival of the fittest, and are suitable for multimodal and multiobjective problems (Holland, 1975a; Goldberg, 1989). This class of optimization approaches is further reviewed in CHAPTER 4.

2.4.2.2 Artificial Intelligence Approaches

Artificial intelligence (AI) approaches have numerous applications in the field of controls, robotics, forecasting, pattern recognition, pharmaceutical, signal processing, power systems, manufacturing, optimization, and social/psychological sciences (e.g., Zhu et al., 1999; Hafner et al., 2000; Kalogirou, 2003; Mellit and Kalogirou, 2008). Little work has been done in the area of gas turbine blade design optimization using AI approaches. A few researchers propose hybrid techniques, where evolutionary algorithms are combined with artificial neural networks which are carefully trained to optimize the gas turbine blades and turbine stages (Mengistu and Ghaly, 2007; Kosowski et al., 2009).

2.5 Multiobjective Optimization

Optimization is defined as the process of solving problems in which the main intention is to maximize or minimize an objective function by systematically selecting random values of real and/or integer decision variables within the range prescribed. During the optimization procedure, the process of obtaining the optimal solution for a problem with single objective is called single objective optimization. However, in reality problems more often involve the consideration of multiple and often conflicting objectives. Multiobjective optimization problems (MOOPs) consider more than one objective function. If the objectives are in conflict, then there is no one best solution exists, but a set of the best compromise (tradeoff) solutions. A multiobjective optimization problem can be represented has the following general form:

$$\min\ (\max)\ \mathbf{f}(\mathbf{x}), \tag{2.1}$$

where $\mathbf{f}(\mathbf{x})$ is vector of m number of objective functions needs to be optimized, *i.e.*, $\mathbf{f}(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_m(\mathbf{x}))$, and solution $\mathbf{x}$ is a n-dimensional vector of decision variables that are real or integer or both. Eq. 2.1, which can be converted to a minimization / maximization problem with no loss of generality, is typically subject to the constraints:

$$\mathbf{g}_j(\mathbf{x}) \leq \mathbf{b}_j,\ j = 1, 2, \ldots, k, \text{ and} \tag{2.2}$$

$$a_i \leq x_i \leq b_i,\ i = 1, 2, \ldots, n, \tag{2.3}$$

where b is a k-dimensional vector of inequality constraints. Eq. 2.3 restricts the values of each decision variable x_i between a lower (a_i) and upper (b_i) bound. Like the decision variable space, the objective functions are also constitute a multidimensional space corresponding to the decision variable space and is called the objective space Z (see Figure 2-2).

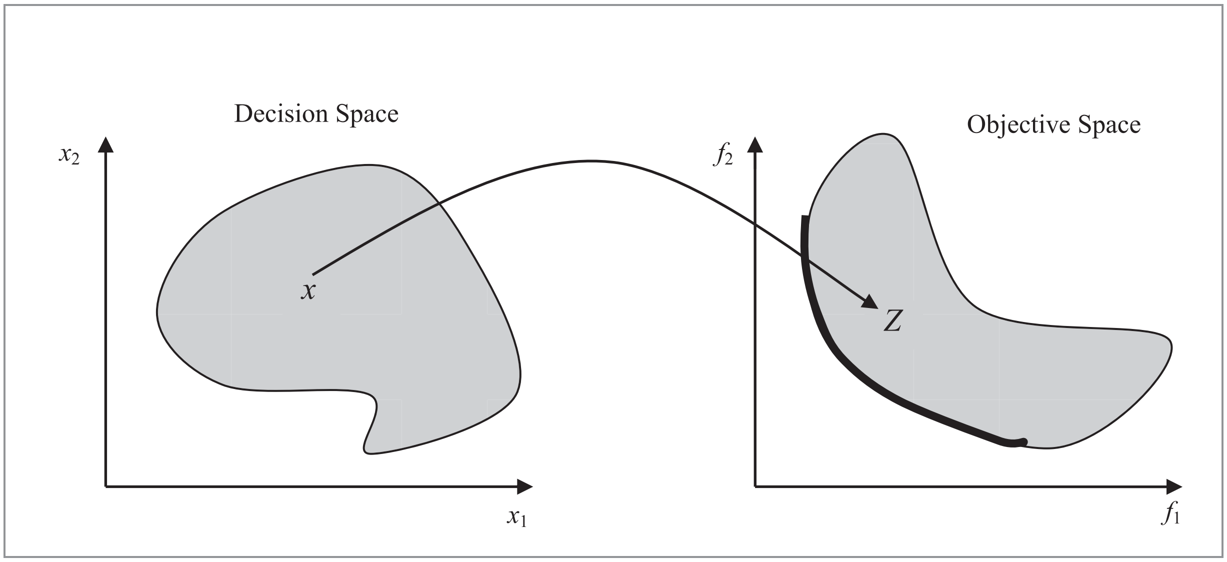


Figure 2-2: Illustration of the decision variable space and corresponding objective space (Deb (2001)

2.5.1 Multiobjective Optimization in Gas Turbine Internal Cooling System Design

In the last 50 years, a wide array of research has been conducted in the area of gas turbine blade cooling. Researchers use analytical, computational and experimental methods to improve cooling techniques for gas turbine. Recent monographs focusing entirely on the gas turbine heat transfer phenomena and associated cooling technology is provided by Goldstein (2001) and Han et al. (2000). Han (2004) also reviews turbine blade cooling techniques and addresses the state-of-the-art reviews of gas turbine blade cooling techniques and heat transfer methods.

The use of multiobjective optimization in heat transfer problems is a relatively new research area of focus and has been the point of interest only in the last few years. In particular, the last few years have seen a sharp increase of heat transfer related optimization using evolutionary algorithms (EAs). Gosselin et al. (2009) review the utilization of multiobjective optimization using genetic algorithms, the more popular representative of the family of EAs, in heat transfer problems.

One of the well-known methods to improve heat transfer (i.e., enhance material cooling) in a channel flow is to roughen the surfaces in the blade's internal cooling channels so that the surface area increases and enhances cooling. Gas turbine researchers study different design configurations of blade internal cooling channels to enhance the cooling process. Pin-fins, ribs and dimples on solid surfaces (Figure 2-3 (a), Figure 2-3 (b) and Figure 2-3 (c), respectively) are usually used in cooling channels to facilitate heat transfer augmentation. These prevent the development of thermal boundary layer and velocity boundary layer between the blade surface and the coolant flow, and increase the creation of turbulent kinetic energy, thus enhancing turbulent heat transfer (Ligrani et al., 2003).

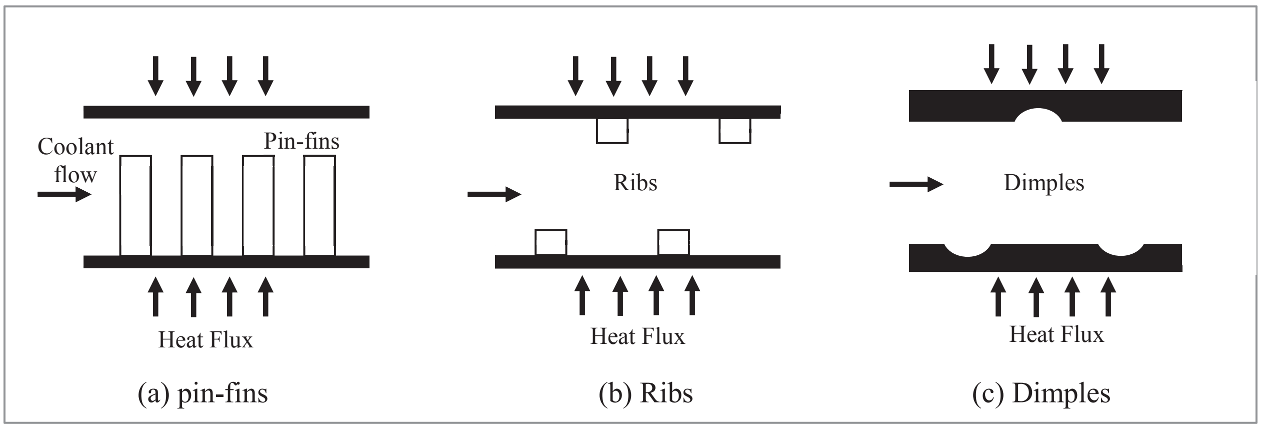


Figure 2-3: Different design configurations for blade internal cooling channels

The use of pin-fins or ribs (see Figure 2-3) to enhance the cooling inside the blade poses other risks such as a decrease in secondary air (coolant) pressure and a decrease in the velocity of coolant flow. Thus, a design optimization process capable of addressing multiple design objectives simultaneously can be a suitable tool in such conditions. The application of multiobjective design optimization to internal cooling channels not only helps enhance the blade cooling, but it can eventually be used in other areas such as heat exchanger/heat sink design, where cooling channels need to be optimized. For example, micro heat exchangers in micro-electromechanical systems (MEMSs) face limitations of space and power to drive cooling systems, which are used in avionics and electronic circuit board for heat dissipation. Foli et al. (2006) perform the shape optimization of micro heat exchangers and estimate the best geometric parameters by attempting to maximize the heat transfer and minimize the pressure drop as two objective functions. The optimized heat exchanger obtained in this method yields heat transfer greater than those obtained by the traditional approach. Husain and Kim (2008) demonstrate the optimization of a micro-channel heat sink using a hybrid multiobjective evolutionary approach. In this study, they consider two performance measures - thermal resistance and pumping power - where both are to be minimized.

Chattopadhyay et al. (1999) develop a multiobjective optimization procedure to optimize the outer shape and cooling holes location on the gas turbine blades to achieve efficient film cooling. In their study, blade average temperature and maximum temperature are chosen as the two main objective functions. These objective functions are then converted into single composite function by summing each objective function multiplied by a weighting factor. The weighting factors are subjectively decided based on the designer's experience or discretion.

Muller et al. (2001) use an evolutionary algorithm to optimize the blade design to enhance film cooling on the blade outer surface. They consider the minimization of the mass flow rate of the coolant, $\dot{m}_c$. The researchers also consider blade temperature as an objective. However, they impose mean, upper and lower bounds on the blade surface temperature using constraints thereby transforming the multiobjective problem to a single objective problem with a composite objective function. It is important to note that the impact on the pressure of the secondary cooling flow is not considered in their study.

Li and Kim (2008) use a multiobjective optimization approach for the shape optimization of pin-fins in three-dimensional heat exchanger channels with elliptic-shaped pin-fin arrays. The aims here are to suggest the best geometric shape of the pin-fins and to assess the interactions between the two objectives – maximizing the heat transfer coefficient and minimizing the coolant pressure drop in the cooling channel. The authors use a multiobjective evolutionary algorithm (MOEA) to find the set of Pareto optima. In a similar study, Samad et al. (2008) propose a staggered array of dimples printed on opposite surfaces of a three-dimensional cooling channel and optimize the shape of the dimples with a hybrid multiobjective evolutionary algorithm to enhance the cooling effectiveness. Two objectives considered in this research investigation are also maximizing heat transfer coefficient and minimizing coolant pressure drop. Both Li and Kim (2008) and Samad et al. (2008) used ε-constraint strategy where one objective is optimized treating the other as equality constraint and the process is repeated for the other objective. This process gives two new sets of optimal solutions to choose from. It is also evident from this approach that, the two objective functions considered are not subjected to optimization simultaneously.

There is limited work that addresses gas turbine blade internal cooling design optimization. Roy et al. (2002) attempt to optimize a turbine blade cooling system design, where their study mainly focuses on handling the presence of complex inseparable function interaction among its decision variables. They propose an evolutionary-based multiobjective optimization algorithm called Generalized Regression Genetic Algorithm (GRGA). Their study shows that

GRGA successfully handles complex inseparable function interaction and gives a range of feasible designs from which one can be chosen based on a designer's preferences. The authors consider two objectives for optimization – minimization of coolant mass flow rate and minimization of the blade metal temperature.

The optimization of cooling channel is studied by Kim and Kim (2002), who consider the optimization of internal cooling channels with straight rectangular ribs (Kim and Kim, 2004a), V-shaped ribs (Kim and Lee, 2007b) and the angle of the ribs (Kim and Kim, 2004b). They identify the values of geometric design variables with the objective function defined as a linear function of heat transfer coefficient and friction drag coefficient (a surrogate measure for pressure drop). They suggest that using a numerical approach presents a reliable way of designing optimized heat transfer surfaces. It is important to note that the two objectives considered in their study are heat transfer coefficient and secondary air flow pressure drop. However, these two objectives are combined to form a composite function using a vector of subjective weights. The selection of the weights is based on a designer's experience, which could lead to errors in optimization if the weights are not carefully selected.

2.6 Summary

In summary, there is limited work that addresses the blade internal cooling design optimization. Further, it can be concluded that the gas turbine community has yet to take full advantage of multiobjective optimization techniques in the design process using evolutionary approach. No researcher has formally studied blade internal cooling channel optimization and computational fluid dynamics and heat transfer analysis for different internal cooling channel design configurations of ribs in the presence of more than two objectives and also no researcher considered two or more independent objectives for simultaneous optimization.

CHAPTER 3:
OVERVIEW OF HEAT TRANSFER AND FLUID FLOW SIMULATION

3.1 Introduction

Over the last two decades, simulation has become a standard industrial tool for the design, analysis, and performance evaluation of engineering systems involving fluid flow and heat transfer phenomena. The process of using computers to study fluids that are in motion, and how the fluid flow behavior influences heat transfer in the systems numerically is called computational fluid dynamics (CFD) analysis (Anderson, 1995; Tu et al., 2008). The use of CFD has been driven by the increased availability of state-of-the-art commercial CFD software and inventions and by advances in computational capability of digital computers at low cost. Particularly, simulation minimizes lead times and costs in design, development and manufacturing substantially compared to an experiment-based approach and offers the ability to solve a wider range of complicated problems where an analytical approach is lacking. The coupling of heat transfer and fluid flow simulation and analysis is common practice in CFD to study how flow behavior influences heat transfer, and design more efficient systems by optimizing design variables. The following sections of this chapter provide a brief introduction on the physics and mathematical governing equations involved in different methods of heat transfer and fluid flow analysis. Readers who are familiar with CFD, fluid flow behavior and numerical simulations may proceed directly to CHAPTER 4 without loss of continuity.

3.2 Heat Transfer

Heat transfer is a discipline of thermal engineering that studies the exchange of heat from one physical system to another. For heat transfer to take place there must be a temperature difference between two regions. Thus, the heat flows from the high temperature region to the low temperature region. The numerical simulation of heat transfer determines the temperature field for varying geometric and fluid characteristics. There are three main modes of heat transfer - conduction, convention and radiation (Incropera et al.,1996).

3.2.1 Conduction Heat Transfer

Conduction heat transfer is the transfer of thermal energy from the more energetic particles of matter to the less energetic particles of matter through the interaction of the particles. Here, there are more energetic particles characterized with higher temperatures than neighboring particles with less energy. When the particles collide, a transfer of energy from the more energetic particles to the less energetic particles occurs. Conduction occurs in all forms of matter, e.g., solids, liquids, gases and plasmas, due to atomic and molecular activity. In solids, it is due to a combination of random translational, rotational and vibrational motion of the molecules in a lattice with the energy transported by the free electrons.

3.2.2 Convection Heat Transfer

In a broad sense, convection heat transfer is the transfer of thermal energy from one place to another via the movement of fluids (i.e., liquids and gases). However, convection heat transfer actually describes two mechanisms that are the combined effect of conduction (molecular motion), and heat transfer by bulk fluid flow. The presence of bulk or macroscopic motion of the fluid enhances the heat transfer between fluid and solid surface. Convection phenomenon can be found in many applications. In this research investigation, the focus is convection heat transfer, which occurs between a fluid in motion and a solid surface when the two are at different temperatures (Incropera et al., 1996; Anderson, 1995).

3.2.3 Radiation Heat Transfer

Thermal radiation is electromagnetic energy emitted by matter that is at a higher temperature compared to its surrounding temperature. Although most research investigations focus on radiation from solid surfaces, emission may also occur from liquids and gases. Regardless of the form of matter, the emission may be attributed to changes in the electron configuration of the constituent atoms or molecules. While the transfer of energy by conduction or convection requires the presence of a material medium, radiation does not. In fact, radiation transfer occurs most efficiently in a vacuum.

3.3 Fluid Dynamics

Fluid dynamics is a sub-discipline of fluid mechanics that study fluids (i.e., liquids and gases) in motion. Further fluid dynamics study the effect of the forces on fluid motion, which can be classified as: (1) fluid statics, which is the study of fluids at rest, and (2) fluid kinetics, which is the study of fluids in motion. Fluid dynamics is an active field of research with complex unsolved or partially-solved problems. It is of significant importance to solve fluid dynamics problems in order to design systems that interact with fluids, such as aircrafts, ships, turbines, heat exchangers, etc. The solution to fluid dynamics problems typically involves finding parameters of the fluid, such as temperature, velocity, density, and pressure, as a function of space and time. Due to its complexity, sometimes it is best solved by numerical methods, using computers and is thus called computational fluid dynamics.

CFD begins with the definition of equations that govern fluid flow. These equations are partial differential equations that govern the conservation of mass flow, momentum flow and energy flow through a medium (i.e., solid, gas or liquid). These equations combine to form the Navier-Stokes Equations, which are not solvable analytically, except only in limited number of cases. However, an approximate solution can be obtained using a discretization process that converts and solves the partial differential equations by a set of algebraic equations (Tu et al., 2008). The resulting algebraic equations relate to small sub-volumes within the flow at a finite number of discrete locations and compute the values of the flow-field variables. There are number of discretization techniques that can be used to solve partial differential equations. The most popular and often used are: (1) the finite volume method (FVM) and (2) the finite difference method (FDM), Figure 3-1 shows the overview of computational solution process. Commercially-available CFD simulation software use any one of these discretization methods to solve the governing equations.

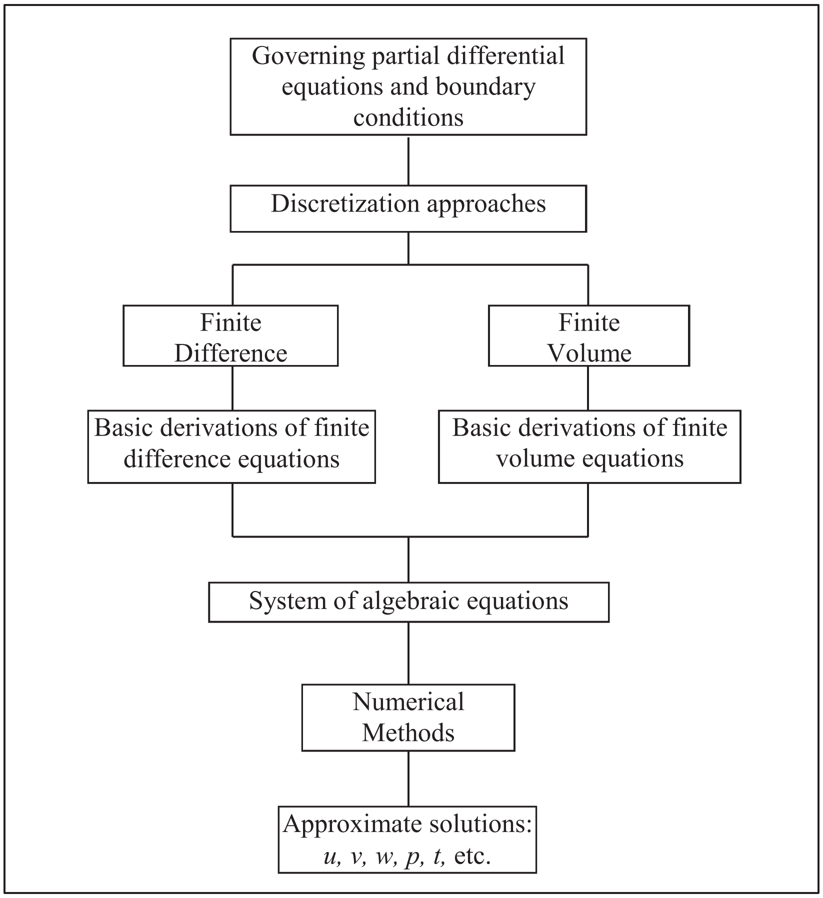


Figure 3-1: Overview process of the computational solution procedure (Tu et al., 2008)

3.4 Heat Transfer and Fluid Flow Governing Equations

The governing equations used in fluid flow and heat transfer are mathematical expressions of the conservation laws of physics. The type and number of equations used in numerical analysis of a model depend on the type of flow and heat transfer conditions and the type of parameters evaluated. The three main governing equations used in CFD are: (1) continuity, (2) momentum and (3) energy equations (Anderson, 1995; Incropera et al., 1996). Their physical laws are defined as:

- *Continuity:* Law of Conservation of Mass

- *Momentum:* The rate of change of momentum equals the sum of the forces acting on the fluid; derived from Newton's Second Law.
- *Energy:* The rate of change of energy equals the sum of the rate of heat conduction and the rate of work done on the fluid; derived from the First Law of Thermodynamics.

These equations are independently constructed by Navier (1827) and Stokes (1845) and are referred to as the Navier-Stokes Equations. In computational analysis of internal cooled gas turbine blades, the parameters such as velocity, pressure and temperature are evaluated along with turbulence models that influence fluid flow and heat transfer. Therefore, it is important that the governing equations considered must consist of fluid flow, energy and turbulence models to solve or predict physical phenomenon of fluid motion and heat transfer. The following sections provide brief description of these equations in the compact Cartesian notation without delving into the derivation of these equations as the derivations of these equations are beyond the scope of this research investigation.

3.4.1 Conservation of Mass

Conservation of mass is based on the law that is pertinent to fluid flow. Conservation of mass states that, matter may neither be created nor be destroyed. Applying conservation of mass to an arbitrary three-dimensional (3D) control volume fixed in space and time, the conservation equation can be expressed as

$$\frac{\partial \rho}{\partial t} + \frac{\partial (\rho u)}{\partial x} + \frac{\partial (\rho v)}{\partial y} + \frac{\partial (\rho w)}{\partial z} = 0 \tag{3.1}$$

where the fluid velocity at any point in the flow-field is described by the local velocity components u, v, and w which are in general, functions of space (x, y, z) and time t.

3.4.2 Momentum: Force Balance

The momentum equations are derived from Newton's Second Law of Motion, which states that the sum of the forces acting on the fluid element must be balanced. These forces equal the product between its mass and acceleration of the fluid element. By applying Newton's Second Law on a 3D fluid element and balancing the forces in all three directions, the following equations can be derived

$$\frac{\partial u}{\partial t}+u\frac{\partial u}{\partial x}+v\frac{\partial u}{\partial y}+w\frac{\partial u}{\partial y} = -\frac{1}{\rho}\frac{\partial p}{\partial x}+\frac{\mu}{\rho}\frac{\partial^2 u}{\partial x^2}+\frac{\mu}{\rho}\frac{\partial^2 u}{\partial y^2}+\frac{\mu}{\rho}\frac{\partial^2 u}{\partial z^2} \tag{3.2}$$

$$\frac{\partial v}{\partial t}+u\frac{\partial v}{\partial x}+v\frac{\partial v}{\partial y}+w\frac{\partial v}{\partial y} = -\frac{1}{\rho}\frac{\partial p}{\partial y}+\frac{\mu}{\rho}\frac{\partial^2 v}{\partial x^2}+\frac{\mu}{\rho}\frac{\partial^2 v}{\partial y^2}+\frac{\mu}{\rho}\frac{\partial^2 v}{\partial z^2} \tag{3.3}$$

$$\frac{\partial v}{\partial t}+u\frac{\partial w}{\partial x}+v\frac{\partial w}{\partial y}+w\frac{\partial w}{\partial y} = -\frac{1}{\rho}\frac{\partial p}{\partial z}+\frac{\mu}{\rho}\frac{\partial^2 w}{\partial x^2}+\frac{\mu}{\rho}\frac{\partial^2 w}{\partial y^2}+\frac{\mu}{\rho}\frac{\partial^2 w}{\partial z^2} \tag{3.4}$$

Eqs 3.2, 3.3 and 3.4 describe the conservation of momentum in fluid flow and are the Navier-Stokes Equations.

3.4.3 Conservation of Energy

Derived from the First Law of Thermodynamics, the energy equation states that the rate of change of energy within a control volume with respect to time must equal the net rate of heat addition to the fluid within the control volume plus the net rate of work done by surface forces on the fluid. Applying this law to a 3D control volume and using Fourier's Law of Heat Conduction the 3D energy conservation equation is:

$$\frac{\partial T}{\partial t} + u\frac{\partial T}{\partial x} + v\frac{\partial T}{\partial y} + w\frac{\partial T}{\partial z} = \frac{k}{\rho C_p}\left[\frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2} + \frac{\partial^2 T}{\partial z^2}\right] + \frac{1}{\rho C_p}\frac{\partial p}{\partial t} + \frac{\phi}{\rho C_p} \tag{3.5}$$

3.4.4 Turbulence Models

Many fluid flows in significant engineering applications are turbulent in nature. It is generally understood that the Navier-Stokes Equations describe mass and momentum transport, (see Eqs. 3.1 through 3.4), and fully describe the flow physics of Newtonian fluids, including the unsteady and randomly fluctuating behavior that is observed in most fluid flow systems. The presence of 3D and unsteady variations in the flow-field indicates that the flow has lost its stability and has become chaotic and random state of motion, i.e., a turbulent condition. These disturbances may originate from the free stream of the fluid with high velocity, or induced by the surface roughness, where they may be amplified in the direction of the flow, in which case turbulence occurs. The presence of turbulence in the fluid flow is determined by the dimensionless parameter called the Reynolds number, which is ratio of inertia forces to viscous forces in the fluid flow

$$Re = \frac{\rho U L}{\mu} \tag{3.6}$$

where ρ is the density of the fluid (kg/m^3), U is velocity of the fluid (m/s), L denotes characteristics length scale, and μ is viscosity of the fluid (kg/s.m). At low Reynolds numbers, the inertia forces are much smaller than the viscous forces in the flow, which results in the laminar flow. The naturally occurring disturbances are dissipated away due to high viscous forces and the flow remains laminar. At high Reynolds numbers, the inertia forces dominate the flow and are sufficient to amplify the disturbances, and, as a result, a transition to turbulence occurs. The existence of turbulence can be advantageous in the sense of providing mixing and, in turn, increased heat transfer rates. Thus, it is important to study the characteristics of turbulent flow in order to quantify and understand the effectiveness of heat transfer. However, during turbulence, the flow becomes intrinsically unstable with velocity and all other flow properties vary randomly making it difficult to describe theoretically. Engineers are able to build a number of turbulence models to predict turbulence flow with the help of computational processes. The selection of suitable turbulence models is very important in any computational analysis.

Turbulence models can be classified into three main categories based on the underlying theoretical hypothesis: (1) Reynolds Stress Turbulence Models, (2) Eddy Viscosity Turbulence Models, and (3) Large Eddy Simulation models. These models have been well-researched, and the interested reader is referred to Anderson (1995) and Tu et al. (2008) for the theoretical underpinnings and research developments using turbulence and turbulence models.

Of the three categories, Eddy Viscosity models are most commonly used in industry for CFD calculations and, this category further comprises two turbulence models - the *k*-epsilon model and the *k*-omega model. These models have become industry standards and appear to provide the best compromise between numerical effort and accuracy of the turbulence properties. The two-equation turbulence models mentioned above are still an active area of research and new refined two-equation models are still being developed (Tu et al., 2008; Anderson, 1995).

CHAPTER 4:
OVERVIEW OF MULTIOBJECTIVE OPTIMIZATION

4.1 Introduction

Optimization is the study of problems in which the goal is to maximize or minimize a real objective function by systematically choosing the random values of real or integer variables from within a prescribed range of values. The need for the optimization of a system or process arises when the goal is to obtain a solution that minimizes/maximizes an objective function or set of objective functions. During the optimization procedure, the process of obtaining the optimal solution for a problem with single objective is called single objective optimization. An optimization problem that contains more than one objective function, then the process of finding one or more optimal solutions is known as multiobjective optimization. A fundamental difference between single objective and multiobjective optimization lies in the cardinality of the optimal solution set. Readers who are familiar with multiobjective optimization may proceed directly to CHAPTER 5 without loss of continuity.

4.2 General Formulation of a Multiobjective Optimization Problem

In general, many real-world optimization problems consist of multiple conflicting objectives which need to be considered for optimization simultaneously. In such scenarios, there is no single solution that is optimal with respect to all objectives. Instead, there exist a number of solutions called Pareto optimal solutions that are characterized by the fact that an improvement in any one objective can only be obtained at the expense of at least one other objective.

A multiobjective optimization problem can be represented in the following general form:

$$\min (\max) \mathbf{f}(\mathbf{x}), \tag{4.1}$$

where $\mathbf{f}(\mathbf{x})$ is vector of m number of objective functions needs to be optimized, *i.e.*, $\mathbf{f}(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}),\ldots, f_m(\mathbf{x}))$, and solution $\mathbf{x}$ is a n-dimensional vector of decision variables that are continuous or discrete or both. Eq. 4.1, which can be converted to a minimization / maximization problem with no loss of generality, is typically subject to the constraints

$$g_j(\mathbf{x}) \leq b_j, j = 1, 2, \ldots, k, \text{ and} \tag{4.2}$$

$$a_i \leq x_i \leq b_i, i = 1, 2, \ldots, n,, \tag{4.3}$$

where b is a k-dimensional vector of inequality constraints. Eq. 4.3 restricts the values of each decision variable x_i between an upper and a lower bound.

Conventional approaches for solving MOOPs usually scalarize the multiple objectives into a single composite objective function using a vector of user-specified weights. This converts the original multiple objective optimization problem formulation into a single objective optimization problem yielding a single optimal solution. There are many drawbacks of using such traditional process include (Eskandari, 2006):

- The subjective vector of weights that is used for the objective functions greatly influences the final solution;
- There a possibility that some solutions may never be found if the objective space is not convex for minimization problems, or concave, for maximization problems; and
- Conventional approaches may not work effectively if objectives have a discontinuous variable space.

However, these and other shortcomings to conventional approaches have motivated researchers and practitioners to seek alternative approaches that generate a set of Pareto optimal solutions rather than just a single solution. Further, Pareto optimal solutions lead to a dilemma of decision–making, which is the eventual selection of a single solution. In order to obtain a single solution, at the end of the optimization process, a decision-maker (DM) has to make a choice in terms of the importance as well as preference of different objectives. Following a classification by Van Veldhuizen and Lamont (2000), the articulation of preferences may be done either before (*a priori methods*), during (*progressive methods*), or after (*a posteriori methods*) the optimization process.

A priori methods: In these techniques, the user preferences are applied prior to the optimization process. The decision-maker has to enter preferences by creating a priority ranking of the different objectives considered. Preferences are expressed using a composite function which combines individual objective values into a single value. The actual optimization is then carried out on the single composite function, ultimately converting it a single objective function problem. While many *a priori* methods are available, the weighted-sum approach is the most common method.

Progressive method: In this method, the user preferences are used concurrently with the optimization process. During the optimization, progressive preference information is applied by the decision-maker to guide the search process. This method is a continuous learning process where the decision-maker progressively gets a better understanding of the problem and interactively refines his/her preferences to quickly converge to the global optimum. However, this method requires high involvement from the decision-maker during the optimization process.

A posteriori method: The user preferences are applied after the completion of the optimization process when the Pareto frontier has been obtained. After the solutions have been found, the decision-maker then selects a tradeoff solution from the set of Pareto optima based on the decision-maker's discretion. The main advantage of this method is that the results obtained are independent of any decision-making process and remains the same irrespective of changes in the decision-maker's articulation of preferences. This method widely uses evolutionary algorithms to treat each objective functions independent while solving for Pareto frontier. Thus, the algorithms used are called multiobjective evolutionary algorithms (MOEAs) and is further discussed in the sections that follow.

4.3 Solution Dominance Multiobjective Problem Environments

A solution is a Pareto optimal solution if there exists no feasible solution for which an improvement in one objective does not lead to a simultaneous degradation in one (or more) of the other objectives. That solution is a nondominated solution and the corresponding solution set is called the Pareto (or efficiency) frontier. No solution in the Pareto frontier is better than any other solution in the front with respect to all objectives.

For example, in deterministic problem environments, most multiobjective optimization applications are gravitating towards using the nondomination-based approaches due to the limitations of traditional multiobjective methods. Assume that $f_i(\mathbf{A})$ and $f_i(\mathbf{B})$ are the values of objective function i ($i \in \{1, \ldots, m\}$) for two Solution vectors **A** and **B**, where **A** and **B** are n-dimensional vectors of the decision variables. The desire is to minimize each objective function.

In a deterministic problem domain, Solution **A** strictly dominates (is better than) Solution **B** if $f_i(\mathbf{A})$ is less than $f_i(\mathbf{B})$ for each objective function *i.* After a set of tradeoff solutions are found, additional problem-specific high level information about the priorities of various objectives can be used by the user to choose a preferred solution from the set of Pareto optima in which to make a decision.

In stochastic problem environments, the objective function values and/or the decision variables are uncertain but they are described with the expected values and variances. This uncertainty typically results from either the randomness effect involved in the simulation modeling or incomplete knowledge about the underlying optimization problem. An issue that should be considered in the stochastic optimization context is the randomness effect of conflicting performance measures in the simulation models caused by the uncertain nature of different processes of the underlying system. The randomness effect of the performance measures plays an important role in the quality of the obtained results; thus, inefficient methods may lead to incorrect conclusions and improper decisions.

4.4 Multiobjective Evolutionary Algorithms (MOEAs)

Evolutionary algorithms (EAs) mimic natural evolutionary principles based on Darwinian evolution theory on survival of the fittest (Goldberg, 1989; Holland, 1975b). The fundamental difference between classical optimization process and evolutionary methods is that EAs use and evaluate sets (i.e., populations) of solutions iteratively to identify the best solutions. The main idea behind EAs is that populations of candidate solutions with certain attributes are applied to an environment and their fitness is assessed. Some of the individuals are better suited to satisfy the requirement of the environment (i.e., survive) and thus have more chance to be selected for populating future generations of populations of individual solutions. As a consequence, over several generations, poor performing solutions are gradually eliminated while the superior solutions evolve and eventually dominate the population in the later generations. Evolution is accomplished through biological-based reproduction by using biological-like operators on the current solutions (called parents) to generate the new solutions (called children) for the next population. These genetic operators are described in detail in later sections.

There are several advantages that make evolutionary algorithms an appropriate choice for solving multiobjective optimization problems over classical or traditional optimization approaches. One of the significant advantages is that it is a population-based approach and uses a parallel search approach. This implies that if an optimization problem is multiobjective and has multiple tradeoff solutions, an evolutionary algorithm is capable of finding those multiple solutions in its final population that optimizes each objective simultaneously, whereas a classical optimization approach may find only a single solution after solving composite function. Kor (2006) summarizes other major advantages of using MOEAs to solve multiple objective optimization problems, which are as follows:

- *Eliminates inconsistencies during problem formulation:* MOEA results are independent of any *a priori* decision-making process. During problem formulation, the inconsistencies associated with weights selection, user preferences and lack of expertise are eliminated.
- *Flexibility in decision-making:* MOEAs are capable of finding a set of solutions called Pareto optimal solutions. After generating Pareto front, user can then select a solution which fits his preferences. In real world problems, objectives and priorities often under

continuous change based on current conditions and MOEAs allows the user to select a suitable solution to reflect the changes in the preferences.

- *Tradeoff information:* MOEAs provide a set of Pareto optimal solutions that are tradeoff solutions for the conflicting objectives. The nondominated solutions that comprise the Pareto frontier allow flexibility in decision-making and also give insight into the system characteristics. Based on the Pareto frontier, the user can have better understanding of the complexity of the problem and priorities among the conflicting objectives before making well-informed decisions or making further changes to the requirements.
- *Uniform spread of solutions:* MOEAs deal with two spaces – decision variable space and objective space. A uniform spread of solutions along the Pareto frontier can be obtained by defining diversity in both the spaces. MOEAs preserve the diversity of the set of Pareto optima, distributing the solutions evenly across the efficiency frontier, thus avoiding the early dominance of a particularly fit solution that limits the scope of the search.
- *Dependency on starting solutions:* MOEA-based approaches are less dependent on the selection of the starting solutions, and they do not require neighborhood definition.

In MOEAs, fitness assignment is generally based on the concept of ranking based on dominance, whereas the diversity of solutions are usually maintained using crowding distance calculation along the Pareto frontier. In recent years, several multiobjective evolutionary algorithms have been developed to handle MOOPs. Among them, Vector Evaluated Genetic Algorithm (VEGA), Multiobjective Genetic Algorithm (MOGA), Non-dominated Shorting Genetic Algorithm (NSGA) and Niched Pareto Genetic Algorithm (NPGA) are some of the most widely used MOEAs. Surveys and comparisons on the different MOEA methods can be found in references Kunkle (2003). The elitist Non-dominated Sorting Genetic Algorithm II (NSGA II), which is an improved version of NSGA, is currently one of the most popular MOEAs and plays a key role in this research investigation.

4.5 Non-Dominated Sorting Genetic Algorithm II (NSGA II)

The elitist Non-Dominated Sorting Genetic Algorithm II (NSGA II) proposed by Deb et al. (2002), is currently one of the most popular MOEA methods used to solve complex and real-world multiobjective optimization problems. NSGA II is the second generation of the Non-dominated Sorting Genetic Algorithm (NSGA) (Srinivas and Deb, 1994). Some of the salient features of NSGA II are its fast elitist sorting method that involves a combined pool of both the parent and child populations and provides diverse population using an autonomous crowding distance method. NSGA II introduces elitism by comparing the current population of candidate solutions with the previously found best nondominated solutions. In NSGA II, the selection procedure uses two processes: (1) Nondominated ranking and (2) crowding distance assignment. NSGA II is different from other optimization methods in the way it applies the ranking/fitness assignment for selection. In the beginning, all the nondominated individuals in the population are identified and assigned a discrete fitness value equal to its nondominance level, with 1 being the best level. These values also indicate the Pareto front, *f*, to which these solutions belongs. Figure 4-1(a) illustrates this concept with the nondomination rank of each individual solution labeled beside it. All the individuals with same fitness value form a layer of dominated front. Before identifying the second set of nondominated individuals, sharing is done among the first front individuals to ensure a better spread of the individuals. Here, sharing is obtained by crowding distance assignment. The crowding distance is defined as the largest cuboid enclosing the point i without including any other neighboring points in the population. Figure 4-1(b) shows the crowding distance of the i^{th} solution as the average side lengths of the cuboid enclosing it. The population is arranged in descending order of magnitude of the crowding distance values. This procedure is repeated for the remaining individuals until all individuals in the population are sorted into various fronts using their crowding distance. The population is reproduced using crowded tournament selection method. The crossover and mutation genetic operators are used to generate new solutions, and the process continues for a desired number of iterations (called generations). Figure 4-2 shows process flowchart for NSGA II for better understanding of the crowding distance and nondomination rank assignment process.

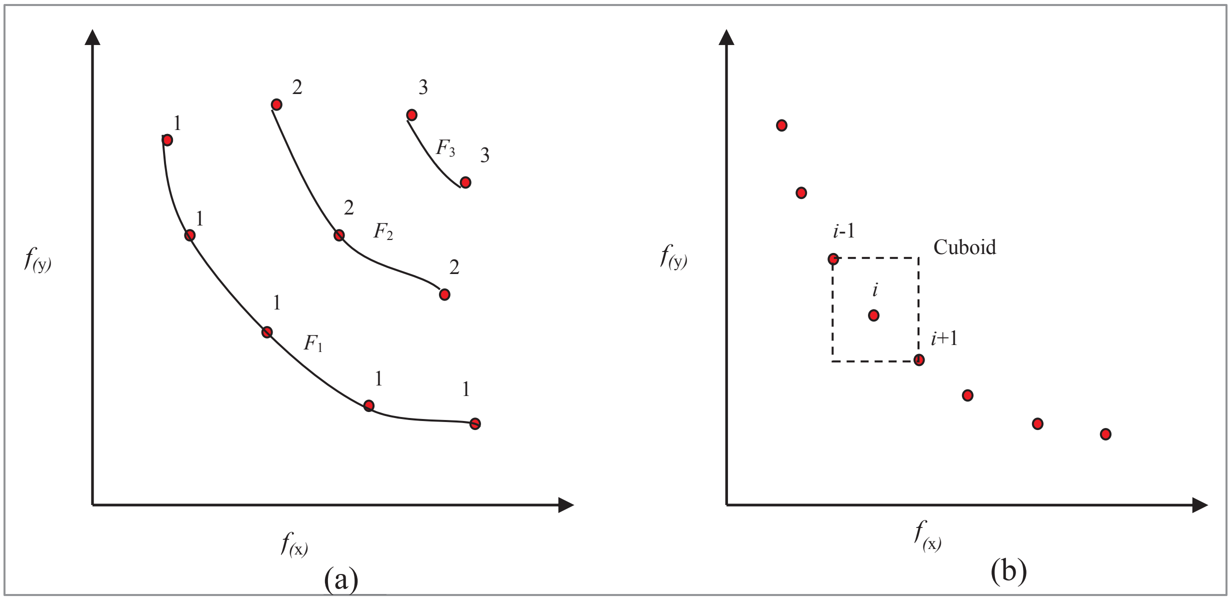


Figure 4-1: (a) The nondomination rank assignment; (b) The crowding distance calculation of NSGA II

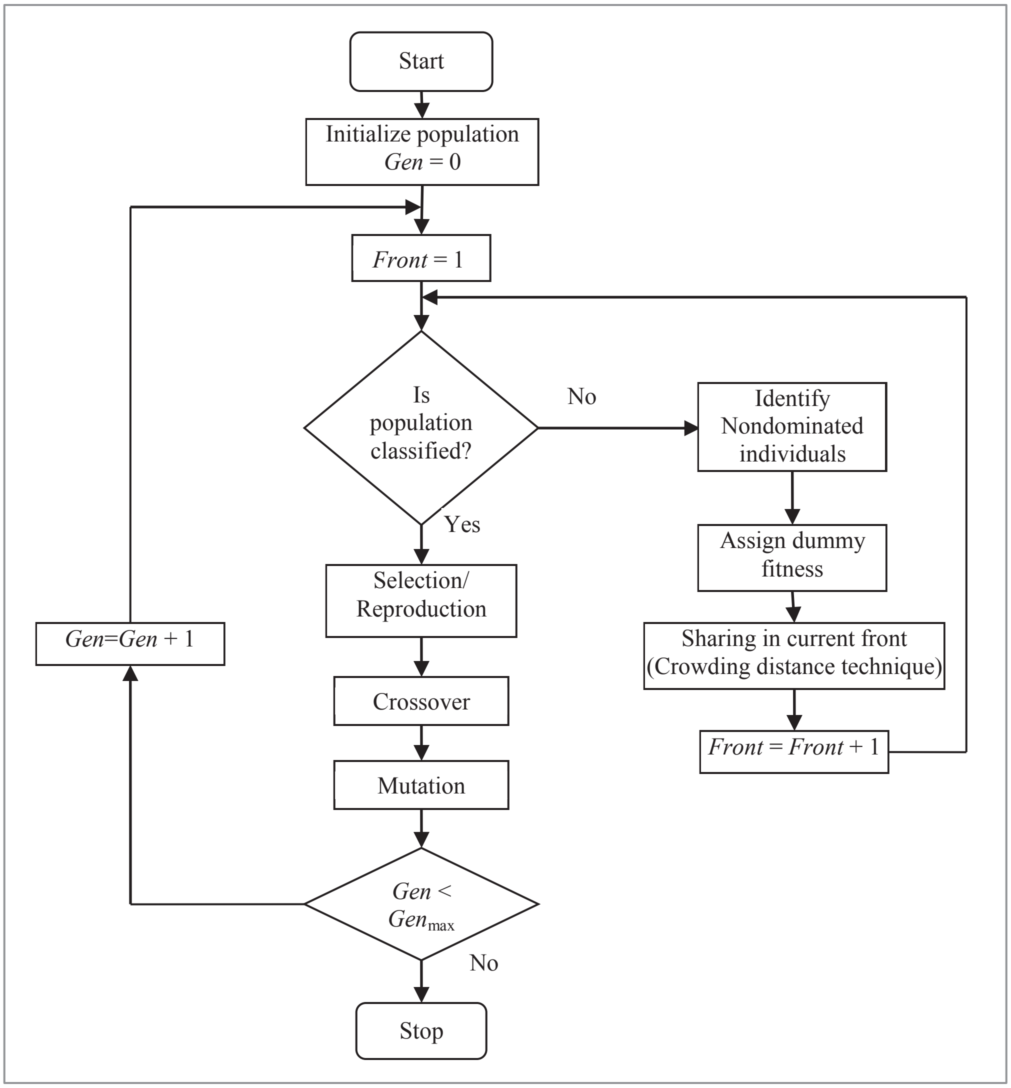


Figure 4-2: A flowchart of the working logic of NSGA II (Deb, 1994)

4.5.1 Reproduction (or Selection) Operator

The primary objective of the reproduction operator is to copy the better performing candidate solutions and discard the poor performing solutions in the population, while maintaining the population size. This is achieved by performing the following tasks:

- Identify the better performing solutions in a population based on their fitness values.
- Make multiple copies of the better performing solutions to create the mating pool.

- Discard poor performing solutions from the population so that the copies of the better performing solutions can be placed in the population.

There are many methods which can be used to achieve the above tasks. Some common methods are tournament selection, ranking selection and fitness-proportionate selection (Goldberg and Deb, 1991). NSGA and NSGA II use the binary tournament selection operator, where comparison operator ($<_c$) compares two solutions from the mating pool and returns the "winner" of the tournament to a separate pool. The tournament selection operator compares two attributes of each solution i before making the selection of the winner. These attributes are:

1) the nondomination rank r_i of a candidate solution i in the population, and
2) the crowding distance d_i of a candidate solution i in the population

4.5.2 The Crossover Operator

A crossover operator, also referred to as the recombination operator, is applied next to the candidate solutions of the mating pool. The crossover operator exchanges information between selected solution pairs (called parent solutions) with a probability of occurrence c. The simulated binary crossover (referred to in the literature as SBX) operator introduced by Deb and Agarwal (1995) is performed in this algorithm.

4.5.3 The Mutation Operator

The crossover operator is primarily responsible for the intensification of the search and the mutation operator allows for diversification of the search to prevent the search process from becoming trapped at a local optimum. After crossover, the newly-generated solutions undergo a mutation operation, where operator changes a 1 to 0, and vice versa, with a mutation probability of occurrence *m*. The polynomial mutation operator introduced by Deb and Goyal (1996) is employed by NSGA and NSGA II in which the probability distribution is polynomial.

CHAPTER 5:
PROPOSED MULTIOBJECTIVE DESIGN OPTIMIZATION FRAMEWORK FOR GAS TURBINE BLADE DESIGN

5.1 Introduction

The overall goal of this research is to investigate and propose an approach that optimizes the gas turbine blade internal cooling channel design to enhance turbulent convective heat transfer while considering multiple design objectives simultaneously. Recall that the specific objectives of this research are to: (1) design a multiobjective procedure for the heat transfer optimization problem; (2) integrate a commercially-available simulation package used to build computational fluid dynamics (CFD) models for the analysis of the flow field and associated heat transfer of different design configurations of gas turbine blade cooling channels; and (3) automate the design optimization framework. In this chapter, the proposed framework for multiobjective design optimization for mechanical components, specifically gas turbine blades and their internal cooling channels is presented.

5.2 Proposed Optimization Framework

The proposed optimization framework for gas turbine blade internal cooling channel design optimization is illustrated in Figure 5-1. The general framework is comprised of: (1) an Optimizer component and (2) an evaluation (Simulator) component. The Optimizer component includes an embedded optimization algorithm that systematically generates candidate designs in terms of the design variable values, and the evaluator component evaluates the candidate designs numerically with respect to the set of performance measures of interest. The simulation can be viewed as a black box with: (1) an input interface that accepts and builds a geometric model (also called a computational model) with new candidate design specifications, and (2) an output interface to communicate design performance measure (i.e., objective function) values to the Optimizer component. Based on the design evaluation results, the Optimizer generates the next set of candidate designs for evaluation. This cycle continues until the optimization termination criteria are met. The subsequent sections provide details of the proposed optimization procedure and components therein.

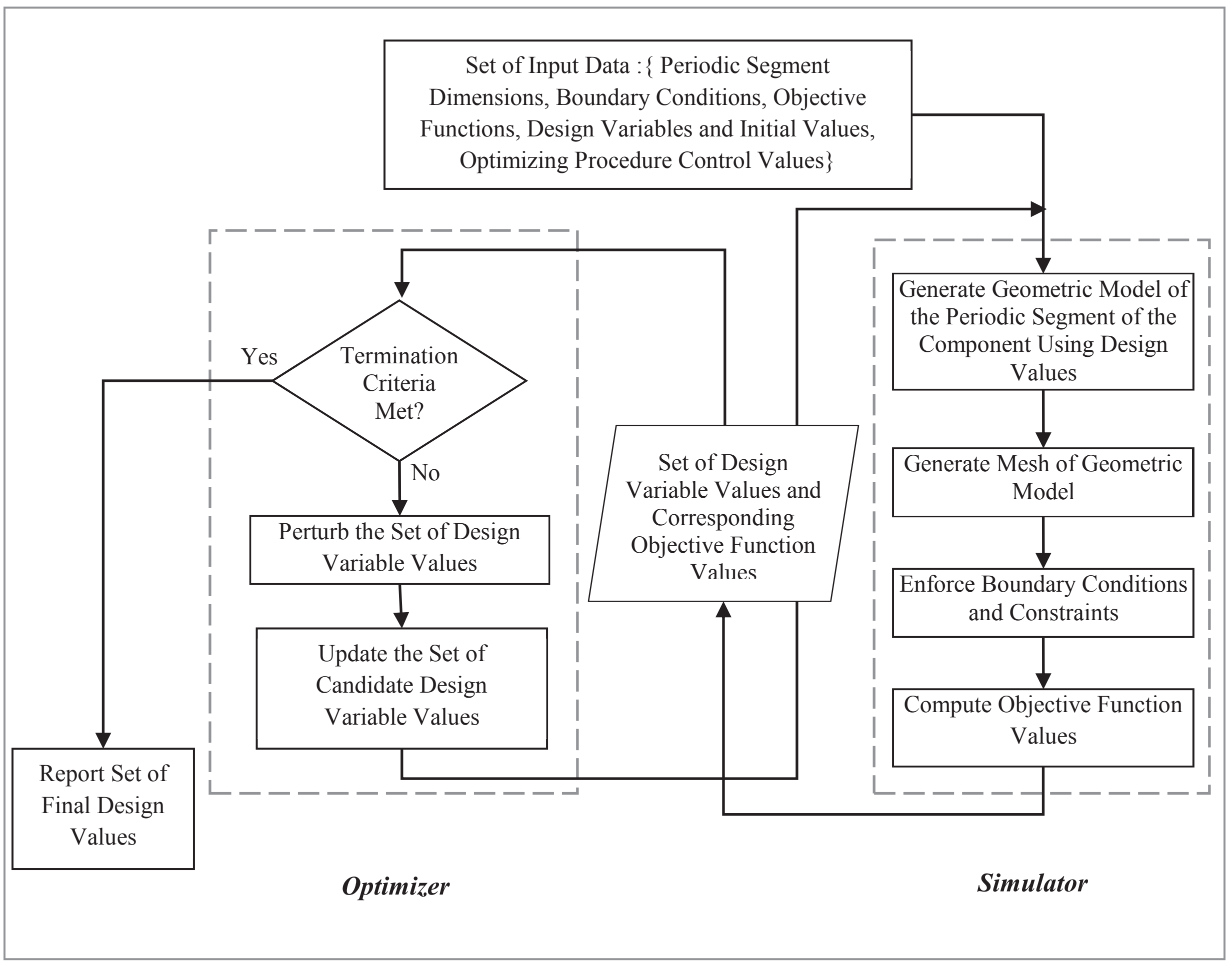


Figure 5-1: Overview of the proposed framework for mechanical component multiobjective design optimization

5.2.1 Input Data Set

It is common knowledge that the choice of the input data and parameters can influence the optimization process as well as the results. The input data are problem-specific and vary depending on type of problem considered. For example, the input data and variables considered for multiobjective process optimization are different compared to multiobjective mechanical component design optimization. Thus, careful identification of problem-specific input data is crucial.

The major steps involved in input data and variable selection for mechanical component design optimization are as follows:

1. Select a critical component that influences the performance and reliability of the entire system;
2. Identify a segment within the component that needs to be optimized;
3. Identify the objectives and constraints that are critical to performance and reliability of the component;
4. Select the design variables and range of values and geometric constraints that influence the objective function values; and
5. Select appropriate physical boundary conditions for the component in order to simulate realistic operating conditions.

The other necessary input parameters are related to optimizer component. These parameters include the sample size of candidate design solutions, the number of search iterations and the search intensification and diversification parameter values. It is important to note that the specific values and ranges of these parameters are problem-specific and are generally chosen by conducting experimental pilot studies in which the values are varied based on the problem and the relative performance of the search intensification and diversification operators.

5.2.2 Simulator Component: Objective Function Evaluation

Objective function evaluation is accomplished via the simulator component. The Simulator component which builds and performs analysis of the computational model based on input data, boundary conditions and ultimately computes the set of objective function values. The steps involved in evaluating objective function values are as follows:

1. The initial geometric model (also called computational model) of selected component/segment is constructed using numerical simulation code.
2. The computational model is discretized (i.e., meshed) into elements that contain material and structural properties, which, in turn, define how the structure reacts to boundary and loading conditions.
3. Boundary conditions are applied on computational model.
4. The Simulator receives and converts a set of design variables values to be evaluated within the computational model.
5. The computational model is solved for the performance measure (i.e., objective function) values iteratively until the solution converges.
6. Objective function values are then exported to the optimizer component.

The above steps are described further in Figure 5-2 with an example of a metallic elbow bracket component that is fixed at one end and subjected to force on the other end. In such problems, a designer's objective is to apply realistic boundary conditions (fixed and force applied) and find (1) the different types of stresses and (2) the location of maximum stresses in the component.

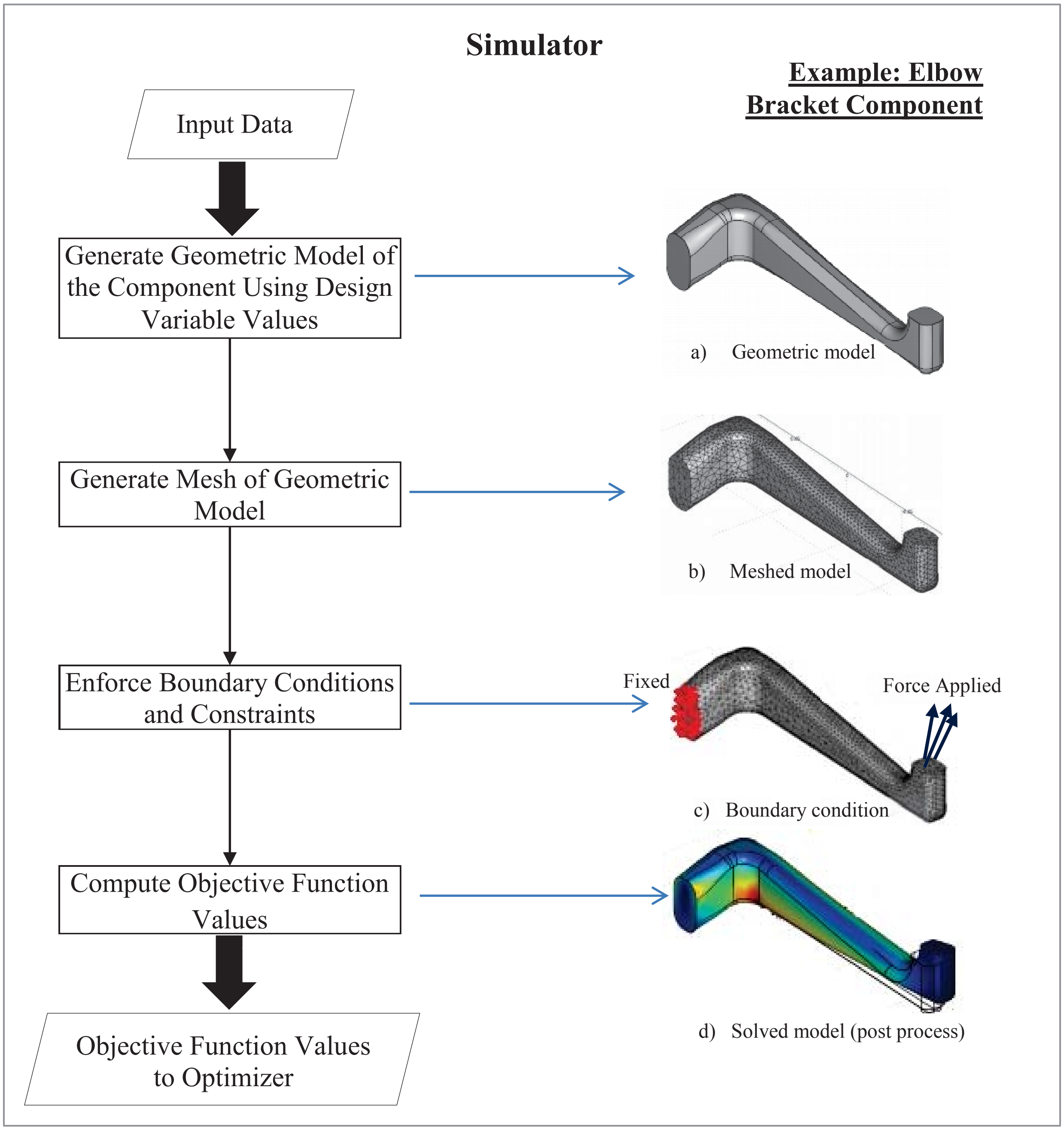


Figure 5-2: The step-by-step procedure of Simulator component using an example.

5.2.3 Optimizer Component: Design Optimization

The Optimizer is integrated with the Simulator in that the Optimizer receives objective function values. Optimizer uses search operators to select best design solutions and apply the search operators to generate a new set of design variable values. The newly-generated design variable values are passed to the Simulator to compute the corresponding objective function values. Figure 5-3 shows a flow chart of step by step process of optimizer process.

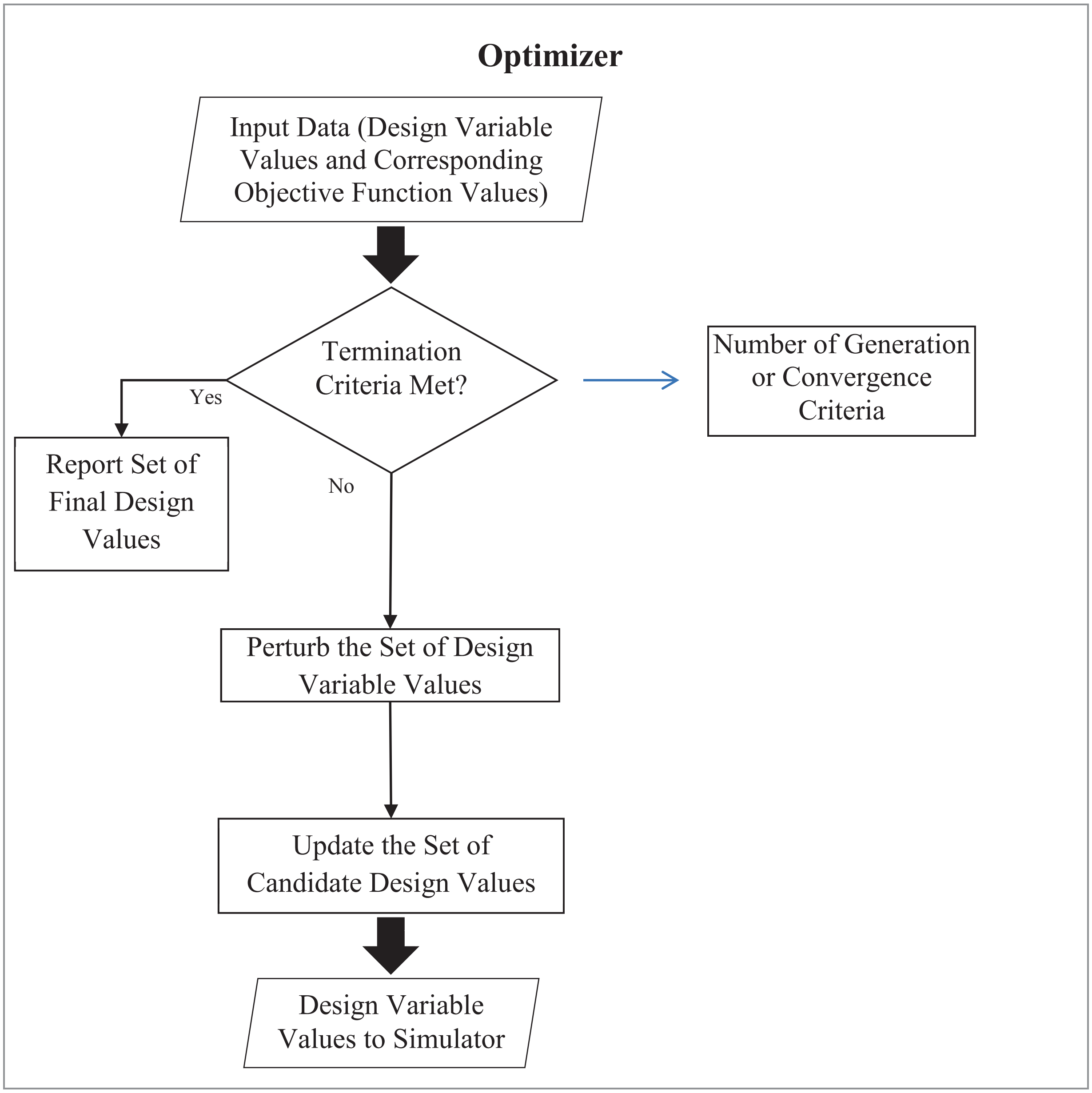


Figure 5-3: The step-by-step procedure of Optimizer process

5.3 Summary

The objective of this research investigation is to design a framework that has the ability to automatically generate a set of design specifications for gas turbine blade internal cooling channels with minimal input data. In this chapter, a framework is presented for the multiobjective design optimization procedure, specifically for gas turbine blade cooling channel design. In the proposed methodology, relatively minimal input data are required. Neither input preferences (i.e., subjective weights) for the objective functions nor any interaction is required during the search to obtain the set of Pareto optimal design solutions.

CHAPTER 6:
COMPUTATIONAL STUDY: TEST APPLICATION, EXPERIMENTAL DESIGN AND PARAMETER SETTING

6.1 Introduction

This chapter presents a description of the design variables, the objective functions, the operating parameters and the control parameters selection procedure for optimization process. This selection criterion is divided into two categories: (1) variables and operating parameters selection for the Simulator (Evaluator), and (2) operating parameters and control parameters selection for the Optimizer. The appropriate parameters and initial conditions for the Simulator are chosen from the existing literature, whereas the parameters and initial conditions for the Optimizer are determined via a pilot study. The pilot study and the final experimental optimization results are obtained by integrating numerical simulation and a multiobjective optimization procedure. For proof-of-concept, a multiobjective evolutionary algorithm (MOEA), i.e., NSGA II, is used to optimize the design variables. In addition, the multi-physics modeling and simulation software COMSOL is used as the Simulator component in the framework. However, the impetus and eventual success of this research investigation is not necessarily predicated upon using these specific approaches.

6.2 Gas Turbine Blade Internal Cooling Channel Design Variables

The optimization of a turbine blade design is complicated by the introduction of secondary cooling air system (refer Figure 6-1). The design of the external airfoil shape of the blade is focused on the section that carries hot gas loads with minimal possible aerodynamic losses. The optimal shape of the blade for ideal aerodynamic performance is often to have a very thin blade, but internal cooling channels demand a certain amount of thickness to accommodate cooling air channels, turbulators (ribs), supporting features, and tip cooling air ejection holes, film cooling holes and slots as shown in Figure 6-1(a) and Figure 6-1 (b).

The scope of this computational study is the design of turbulators whose main purpose is to increase the surface area of blade material in contact with the coolant, thereby promoting turbulence to increase the heat transfer rate. Various turbulators designs include ribs, pin-fins, etc. Figure 6-1(c) shows rib-roughened internal cooling channels, which is the particular focus of the computational study. In this study, ribs within the blade cooling channel solid surfaces are optimized to augment heat transfer and enhance blade cooling. As previously mentioned, ribs prevent the development of a thermal boundary layer and a velocity boundary layer between the blade surface and the coolant flow, and increase the creation of turbulent kinetic energy, thus enhancing turbulent heat transfer. However, the success of proposed mechanical component design optimization approach is not necessarily based upon optimizing ribs only and can be applied to other mechanical component design scenarios.

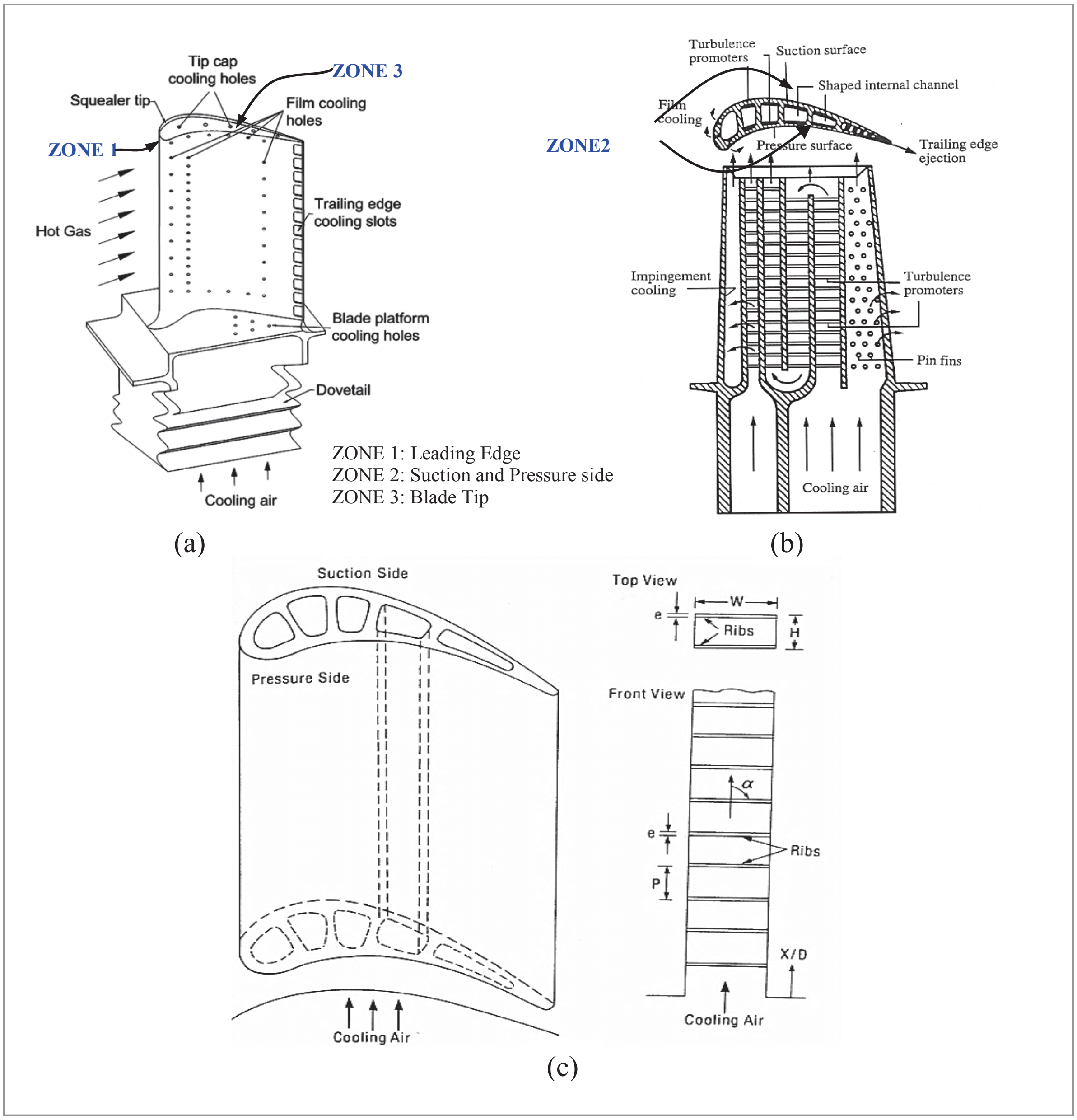


Figure 6-1: Typical coolant channels in turbine blade and internal rib arrangement (Han et al., 2000; Reprinted with permission of the Taylor & Francis Group)

With the focus of the computational study being the design of ribs, then the goal is to optimize the shape of a two-dimensional gas turbine blade cooling channel with periodic ribs mounted on top and bottom wall. The channel is simplified to a two dimensional rectangular channel to minimize the computational effort. A periodic segment of the cooling channel, as shown in Figure 6-2, is considered. The radii (R_1 and R_2) of ribs 1 and 2 (in the periodic segment), and fillet radii (R_3, R_4, R_5 and R_6) between ribs and wall surface are considered as critical design variables that influence the values of objectives. Ribs induce separation and reattachment of flow to enhance the heat transfer by creating turbulent mixing. The heat transfer is greater at the reattachment locations, but it is low at the locations where flow separation takes place due to ribs. The flow separation and reattachment phenomenon is influenced by radii of the ribs.

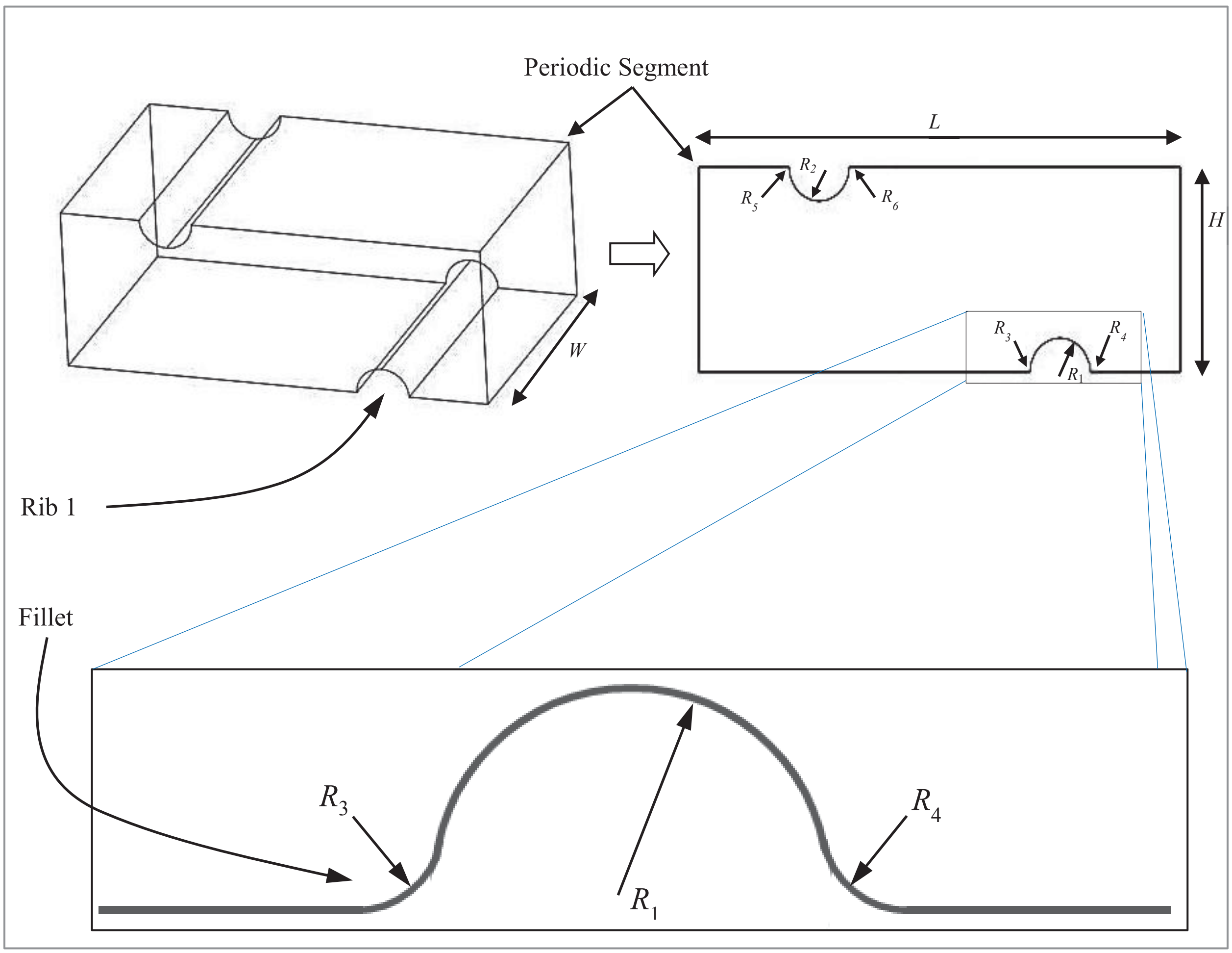


Figure 6-2: Periodic segment of blade cooling channel with design variables

The increase in radii R_1 and R_2 increases size of the ribs, surface area and turbulent mixing inside the cooling channel to enhance the heat transfer from blade to cooling air flow. However, an increase in rib size increases the drop in air flow pressure and also gives rise to more material usage. Fillet radii decreases pressure drop and at the same time increases heat transfer rate by creating smooth surface contact between ribs and blade wall (refer to Figure 6-2 for an enlarged view of cooling channel ribs and fillets). Therefore, variations in these specifications can change the heat transfer coefficient h, the pressure drop Δp and the amount of consumption of blade material.

Length (L), Height (H) and Width (W) of the periodic cooling channel segment are considered not critical and are treated as constant design parameters. These three parameters are fixed in order to maintain the structural integrity of the blade. For instance, an increase in H causes a decrease in the blade's pressure side and suction side wall thickness and an increase in W may cause a decrease in wall thickness between cooling channels. The decrease in these wall thicknesses may compromise the blade strength against thermal as well as mechanical stresses. Hence, H and W are not considered as variables in this investigation, whereas L is length of the periodic segment and it is treated as a constant.

For this research investigation, the initial ranges of the design variables values are identified from empirical results published in the existing research literature. The ranges of the design variables R_1 through R_6 are given in the Table 6-1. Specifically, these ranges are approximated based on experimental results by Han et al. (2000).

Table 6-1: Design variables and value ranges (in meters)

Parameters	Lower Bound	Upper Bound
Radius of Rib 1 (R_1)	0.0010	0.0055
Radius of Rib 2 (R_2)	0.0010	0.0055
Radius of fillet 1 (R_3)	0.0001	0.0004
Radius of fillet 2 (R_4)	0.0001	0.0004
Radius of fillet 3 (R_5)	0.0001	0.0004
Radius of fillet 4 (R_6)	0.0001	0.0004

6.3 Description of the Design Objectives

The gas turbine blade internal cooling channel designs currently in use represent decades of research and practice. New internal cooling channel designs have been found that enhance the cooling effectiveness beyond previous known values, and, in turn, these techniques have led to improvements in blade life in some cases and increased turbine inlet temperature (TIT) to increase the efficiencies in other cases (Moustapha et al., 2003).

Review of the open literature suggests that the traditional process of design optimization for gas turbine blades has matured. Further efforts expended in this direction have not provided significant improvements. As a result, more non-traditional methods such as multiobjective design optimization techniques are new to this field and have become more attractive. These techniques and their introduction offer numerous benefits over the traditional design techniques. The main such benefits are improved efficiency, a shortening of the design time and a significant reduction in human efforts due to fully automated process of design optimization.

Multiobjective design optimization process starts with selection of objective functions that are critical to the performance of the component/system and are directly associated with design variables. In this research investigation, three common, real-world objective functions are considered. The three objective functions considered for this investigation are treated equally important during the optimization process, and they are:

1) Maximize blade cooling effectiveness (*Φ)* by maximizing heat transfer coefficient (*h*) inside cooling channel [W/m^2 K]. Theoretically, it is defined as –

$$h = \frac{N_u k}{D_h}, \tag{6.1}$$

where N_u is the Nusselt number a dimensionless parameter and a measure of the heat transfer rate, k is thermal conductivity [W/m K] and D_h is hydraulic diameter of the channel [m] (channel height is D_h in case of a two-dimensional problem).

2) Minimize air pressure drop (Δp) inside the internal cooling channel of the blade. Theoretically, it is defined as

$$\Delta p = \frac{2 f \rho u_b^2 P}{D_h}, \tag{6.2}$$

where f is a dimensionless friction factor, ρ is the density of air [kg/m^3], u_b is the axial velocity [m/s] and P is rib pitch [m] inside the cooing channel.

3) Minimize rib material usage by maximizing the internal cooling channel cavity area (*A*). Figure 6-3 shows the cavity area and its influence on the amount of material used to form

each rib. In other words, assuming the channel wall thickness remains constant, the larger the cavity area, the smaller the ribs, and the smaller the cavity area, the larger the ribs. This objective can also serve as a surrogate for material cost minimization.

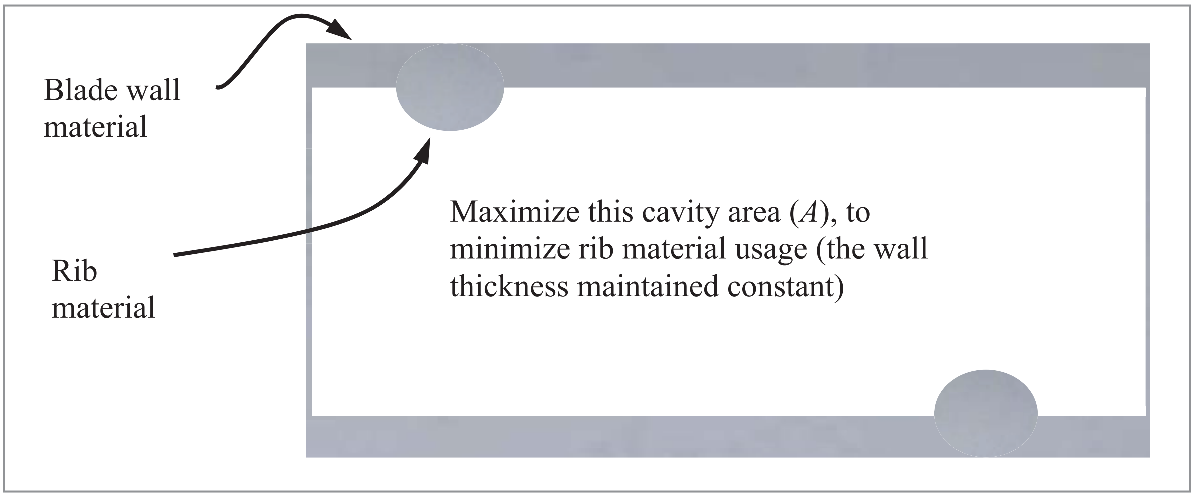


Figure 6-3: Pictorial representation of blade cooling channel segment with wall thickness

Optimized ribs enhance the turbulent convective heat transfer, minimize coolant pressure drop and also minimize material used in blade manufacturing. It is important to note that the three objective functions considered are conflicting in the sense that, satisfying one objective function results in compromise in at least one other objective function. For example, maximization of h is achieved by increasing surface area inside blade cooling channel (using ribs, pin-fins, etc.,) which results in increased Δp and also increased material usage by decreased cooling channel cavity area A. Similarly, minimization of Δp is achieved when the cooling channel has a smooth surface (e.g., without ribs, without pin-fins, etc.), which in turn results in the undesired effect of reducing h, but a reducing material usage A, which is desired effect.

The increase in blade cooling effectiveness allows gas turbine power plants to operate the turbine engines at a higher turbine inlet temperature (TIT), which in turn increases the efficiency of the turbine engine without compromising the life of the blade. Likewise, minimization of Δp inside the blade cooling channel is important to retain enough pressure in the cooling channel for satisfactory ejection of the secondary air flow. If there is insufficient pressure in the cooling air flow, the exit velocity of the coolant is lower than the mainstream air flow, contributing to the loss of efficiency (Park et al., 1984; Moustapha et al., 2003). Lastly, maximization of the cavity area A inside the cooling channel leads to the reduction of the total surface which is directly connected to the material usage inside cooling channel thus minimizing material usage cost (Figure 6-3).

6.4 Parameter Selection for the CFD Simulation

The physical parameters and fluid properties are essential in CFD numerical simulation to predict fluid flow behavior and to know how it influences processes that may include heat transfer, fluid structure interaction and possibly chemical reactions in combusting flows. It is, therefore, important that a designer carefully identifies the underlying flow physics, boundary conditions, and fluid properties that are unique to the particular fluid flow problem.

In this research investigation, COMSOL, a commercially-available CFD tool, serves as the role of the Simulator component in the optimization framework. This section summarizes the physical parameters and fluid properties selected to simulate coolant flow and heat transfer in periodic segment of gas turbine blade internal cooling channel. As previously mentioned in Section 6.2, the physical model considered in this research investigation is simplified to a two-dimensional (2D) cooling channel segment, as shown in Figure 6-4. In numerical simulation, this 2D geometric model is called the computational domain.

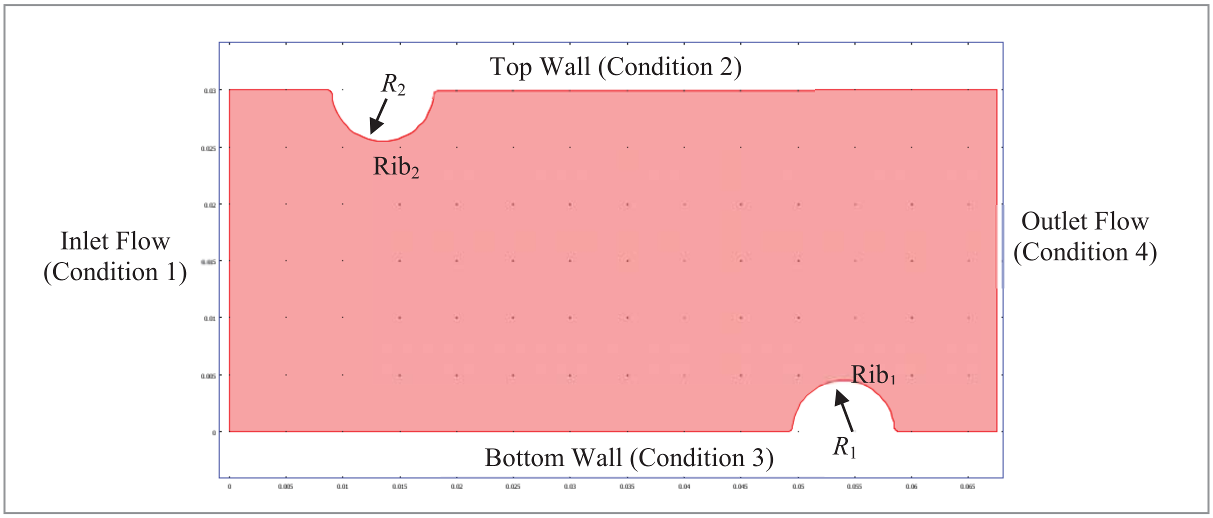


Figure 6-4: Two-dimensional periodic segment of cooling channel with ribs

The flow physics is selected to reflect realistic conditions of cooling channel flow in order to correctly simulate the characteristics of the fluid flow. Here, compressed air (coolant) with non-isothermal and turbulent flow physics is used. Table 6-2 shows the material properties (density, dynamic viscosity) of air at atmospheric temperature and pressure, and these properties are imposed through the graphical user interface of COMSOL.

Table 6-2: Initial subdomain conditions used for the COMSOL numerical simulation

Fluid	Properties
Air Coolant	Density (ρ) = 1.204 kg/m^3
	Dynamic Viscosity μ = 1.983 x 10^{-5} kg/m s

Table 6-3 summarizes initial boundary conditions used to solve objective functions in the COMSOL simulation environment. In Figure 6-4 the cooling channel Inlet Flow (Condition 1) is subjected to a temperature (T) and velocity (u) to create necessary turbulence in the flow. Top and bottom wall (Conditions 2 and 3) are no-slip wall boundary conditions, where fluid velocity is zero. Both top and bottom walls are subjected to thermal load due to their direct contact with hot gas (Figure 6-1a); therefore, they are subjected to a constant temperature boundary condition. At the outlet flow (Condition 4) indicating fluid departure, typically a relative pressure and convective heat flux is imposed. The coolant properties, temperature (T) and velocity (u) are used to mimic the physical representation fluid flow in the cooling channel.

Table 6-3: Initial boundary conditions used for the CFD simulation.

Boundary	Initial / Boundary Condition
Inlet Flow (Condition 1)	Temperature (T) = 293 Kelvin
	Velocity (u) = 10 m/s; Reynolds Number (R_e) ≈ 20,000
Wall (Conditions 2 and 3)	Temperature = 393 Kelvin
	Thermal wall function
Outlet Flow (Condition 4)	Convective heat flux
	Pressure (p) = 0

The boundary conditions are used as initial conditions to solve the governing Navier-Stokes equations (Eqs. 3.1 through 3.5) iteratively to predict approximate fluid flow and heat transfer properties inside the cooling channel.

6.4.1 Computational Fluid Dynamics Simulation

This section presents brief description of steps used in CFD analysis of two-dimensional cooling channels considered in this study. Also presented are contour plots of the simulation results. In general, complete CFD analysis consists of three main steps:

- *Pre-processing*
- *Solver*
- *Post-processing*

Figure 6-5 presents a framework that describes the interconnectivity of the three aforementioned elements within the CFD simulation analysis. The functions of these three elements for the computational model are examined in more detail in the following subsections.

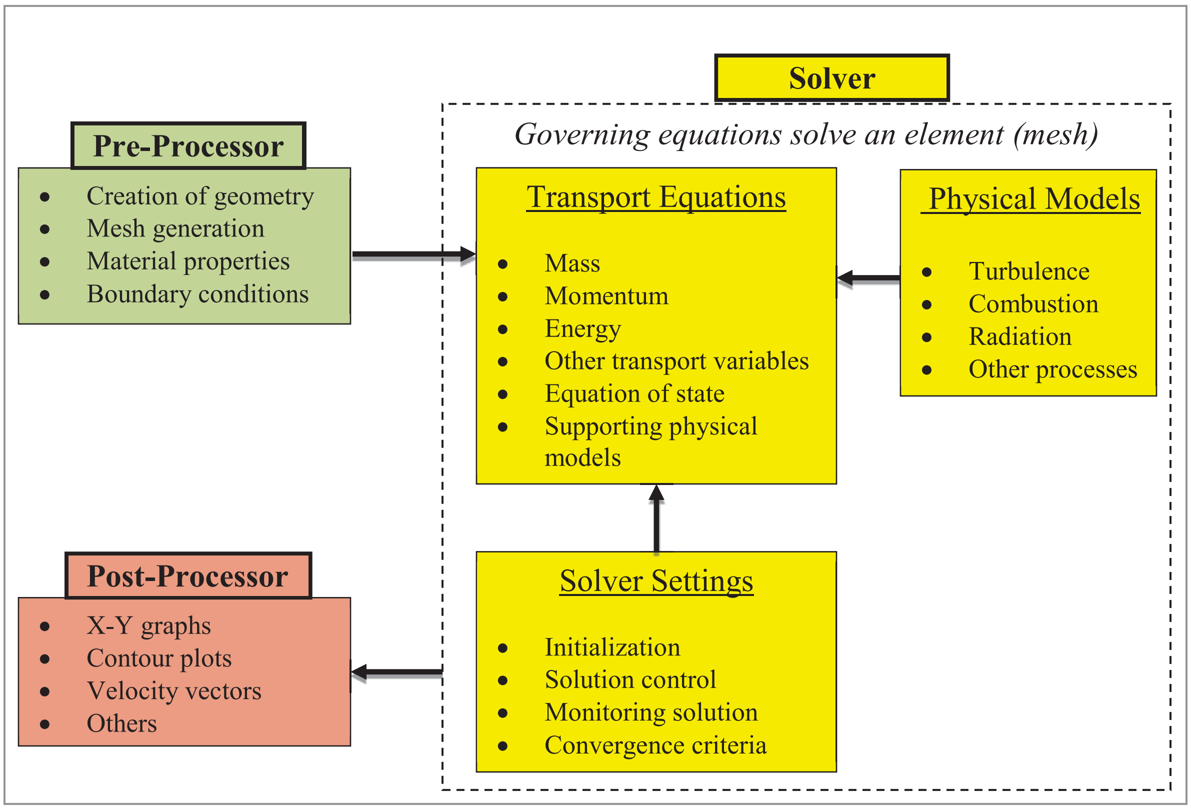


Figure 6-5: The inter-connectivity of the three main functions in CFD simulation framework

6.4.1.1 Pre-Processing

In CFD analysis, Pre-Processing starts with the identification and preparation of physical component for computational analysis. It involves building a computational model using geometric definitions and creation of surface meshes and setup of boundary conditions for fluid and heat transfer analysis.

6.4.1.1.1 Creation of Geometric Model

To simulate and evaluate the heat transfer coefficient h and pressure drop Δp in the blade cooling channel segment, detailed initial geometric design specifications of the segment is needed in advance. The computational model of the periodic segment is built based on these initial geometric features. For a pictorial view of a blade cooling channel, refer to Figure 6-1, which shows a schematic view of typical turbine blade and its cooling channels. A periodic segment selected of a cooling channel for this research investigation is shown in Figure 6-6.

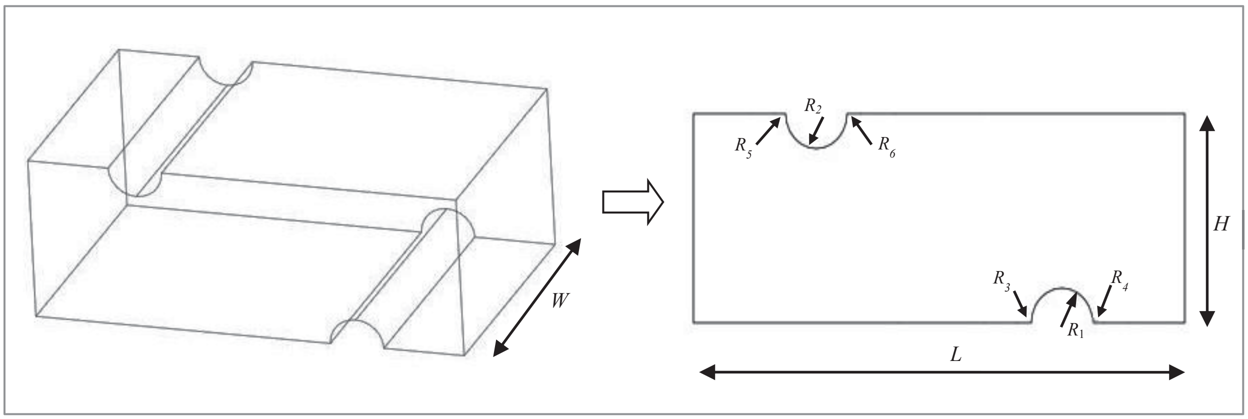


Figure 6-6: Simplified two-dimensional rectangular cooling channel from three-dimensional cooling channel

6.4.1.1.2 Mesh Generation

The second step in Pre-Processing is mesh generation. It is one of the most important steps after the creation of domain geometry. The numerical simulation requires the subdivision of the domain into a number of smaller elements in order to solve the flow physics within the computational domain that has been created; this results in the generation of a mesh (or grid) of elements (cells). The required fluid flows that are described in each of these elements are usually solved numerically to obtain the discrete values of the flow properties such as temperature, velocity, pressure and other parameters of interest. The accuracy of a CFD solution is governed by the number of elements in the mesh within the computational domain. The boundary and intricate geometry is meshed with high density mesh to capture flow and heat transfer parameters that vary with space significantly at these locations. Figure 6-7 shows a meshing of cooling channel using unstructured triangular elements. These elements (triangular) are selected because of their flexibility of mesh generation for geometries having complicated shape boundaries. The ribs and blade walls are meshed with one layer of quadrilateral elements and high density of triangular elements to accurately capture fluid flow parameter which vary drastically at these locations. The Table 6-4 shows mesh statistics used in cooling channel.

Table 6-4: Mesh statistics

Number of Elements	Triangular: 5080 Quadrilateral: 388 Total:5468
Number of Boundary Elements	460
Minimum Element Quality	0.8

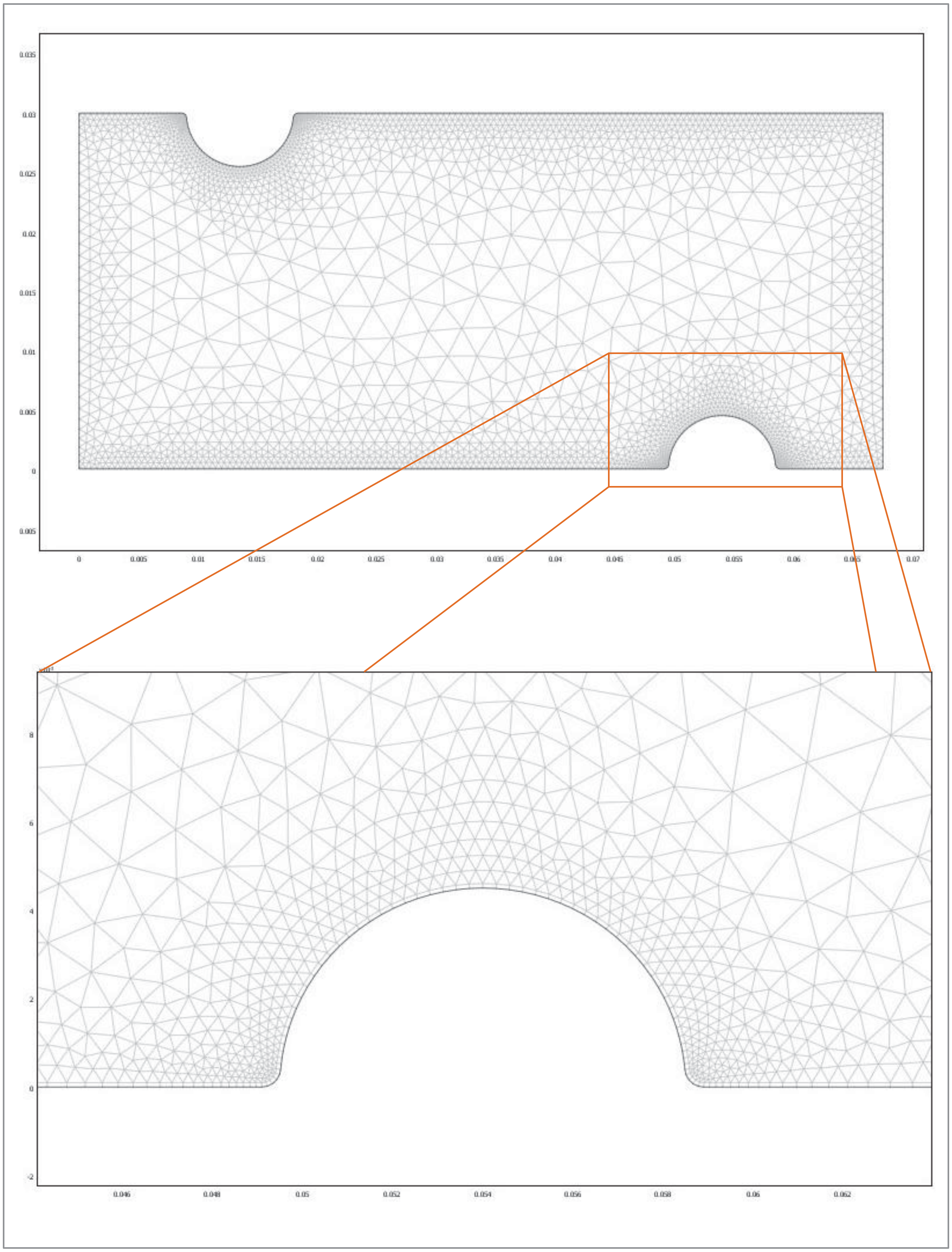


Figure 6-7: Two-dimensional meshed geometry of cooling channel

6.4.1.1.3 Physics and Boundary Conditions

The identification of nature of the problem by its physical process is essential to determine right boundary conditions to mimic the problem environment. This step is last step in Pre-Process stage and deals with application of thermo-physical properties of the coolant from materials library of COMSOL and application of boundary conditions.

Boundary conditions are formal way of applying the initial test conditions to the computational model. These conditions are set of values specified for the behavior of the solution to a set of governing equations at the boundary of the computational domain. Boundary conditions are important in determining the mathematical solutions to physical problems starting from initial values and converge to approximate solutions iteratively. For this research investigation, the boundary conditions are applied to create a turbulent flow and a temperature gradient between coolant and cooling channel walls. Table 6-5 lists boundary condition types, initial values and Figure 6-8 shows application of boundary conditions in the computational domain.

Table 6-5: Boundary conditions

<table>
<tr><th>Boundary</th><th>Initial / Boundary Condition</th></tr>
<tr><td rowspan="2">Inlet Flow (Air)</td><td>Temperature (T_i) = 293 Kelvin</td></tr>
<tr><td>Velocity (u) = 10 m/s; Reynolds Number (R_e) ≈ 20,000</td></tr>
<tr><td rowspan="2">Wall</td><td>Temperature (T_w)= 393 Kelvin</td></tr>
<tr><td>Thermal wall function</td></tr>
<tr><td rowspan="2">Outlet Flow</td><td>Convective heat flux</td></tr>
<tr><td>Pressure (p) = 0</td></tr>
</table>

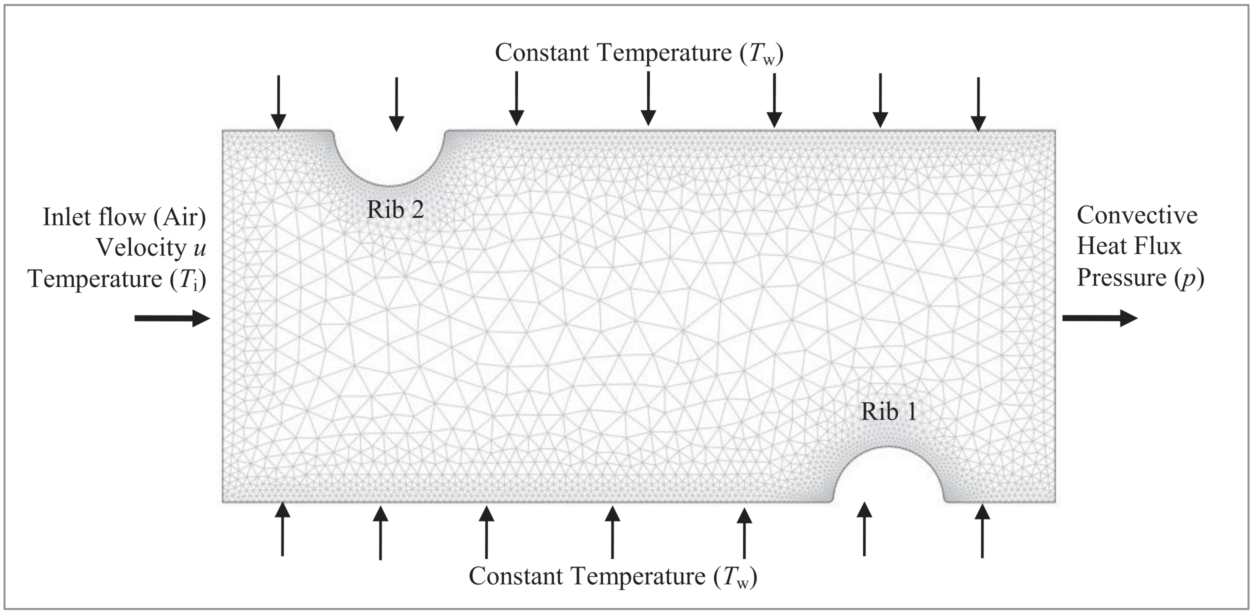


Figure 6-8: Boundary conditions for cooling channel

6.4.1.2 Solver

A CFD solver houses a numerical solution technique such as a) Finite Difference Method (FDM), b) Finite Element Method (FEM), or c) Finite Volume Method. All of these numerical methods perform approximation of the unknown flow variables by means of simple functions and substitute these approximations into governing flow equations and solve iteratively to obtain final approximate solution. The CFD tool COMSOL used in our research uses FEM solver to approximate the flow parameters inside cooling channel.

6.4.1.3 Post-Processing

CFD has a reputation of generating vivid graphic images of processed results. The Post-Processing step in CFD is the interpretation and visualization of these vivid graphic images of simulation results. The multiobjective framework created in this research investigation accepts solutions (objective functions values) in numerical form. To aid our optimization framework a script is developed for COMSOL to calculate objective function values from CFD solution. But for the purpose of understanding CFD graphical results, the remainder of this section presents graphical results of cooling channel along with brief interpretation of the graphs.

Post-processed contour plots of heat transfer and fluid flow simulation are presented. A surface contour plot of the temperature, pressure and heat flux (W/m2) within a computational domain are shown in Figure 6-9, Figure 6-10 and Figure 6-11 respectively. These three plots are post-processed CFD results and are analyzed based on a color spectrum and the intensity of the colors. All the surface plots describe the intensity of a parameter within the computational domain typically varying in color from dark blue to dark red as shown in the legend bar at the right hand side of each plot. Here, the dark blue indicates the minimum value attained by parameter and dark red indicating the maximum value attained by the parameter in the computational domain. For example, Figure 6-9 shows the temperature distribution in the computational domain. At the entrance (the left side boundary), an inlet temperature of 293K (cool air) is applied. The top and bottom wall surfaces are maintained at constant temperature of 393K. From the color plot, it can be concluded that the temperature of the incoming cool air (dark blue) increases in temperature because it picks up heat from the surfaces (i.e., top and bottom) while flowing through the geometric shape (i.e., the cooling channel). This phenomenon of heat transfer from hot surface to cooling air is visible in the figure and is shown by the color gradient present at the top and bottom surfaces. This analysis and interpretation is also true for the other two plots (pressure distribution and heat flux distribution) that follow.

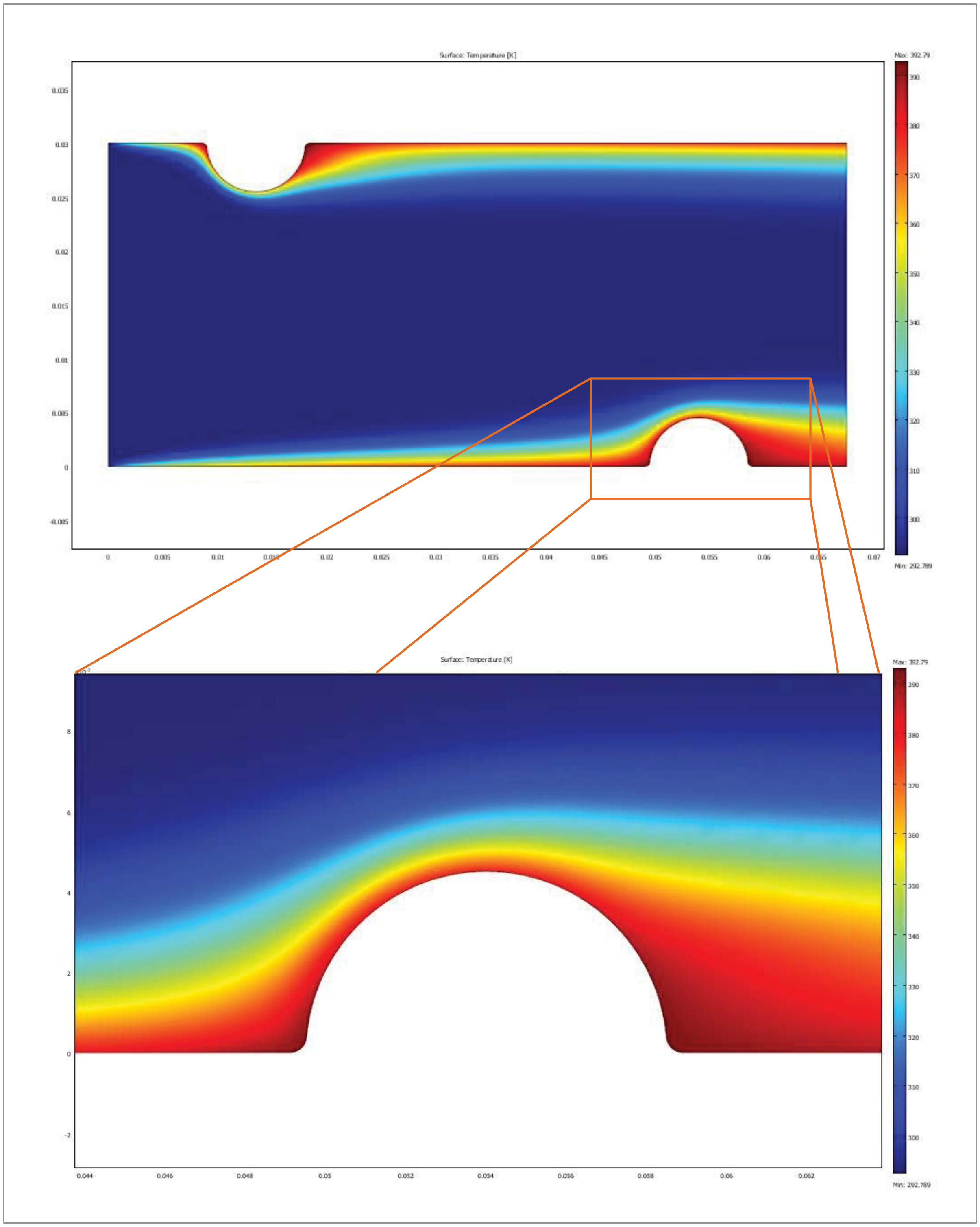


Figure 6-9: Temperature distribution near rib (units are in K)

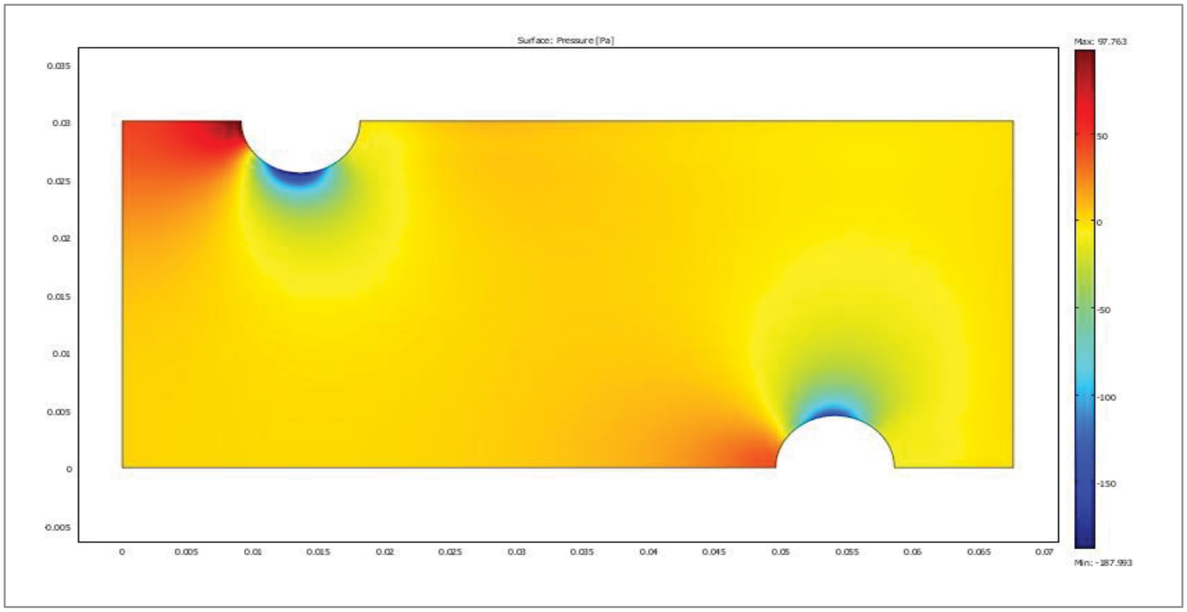


Figure 6-10: Pressure distribution (units are in Pascal)

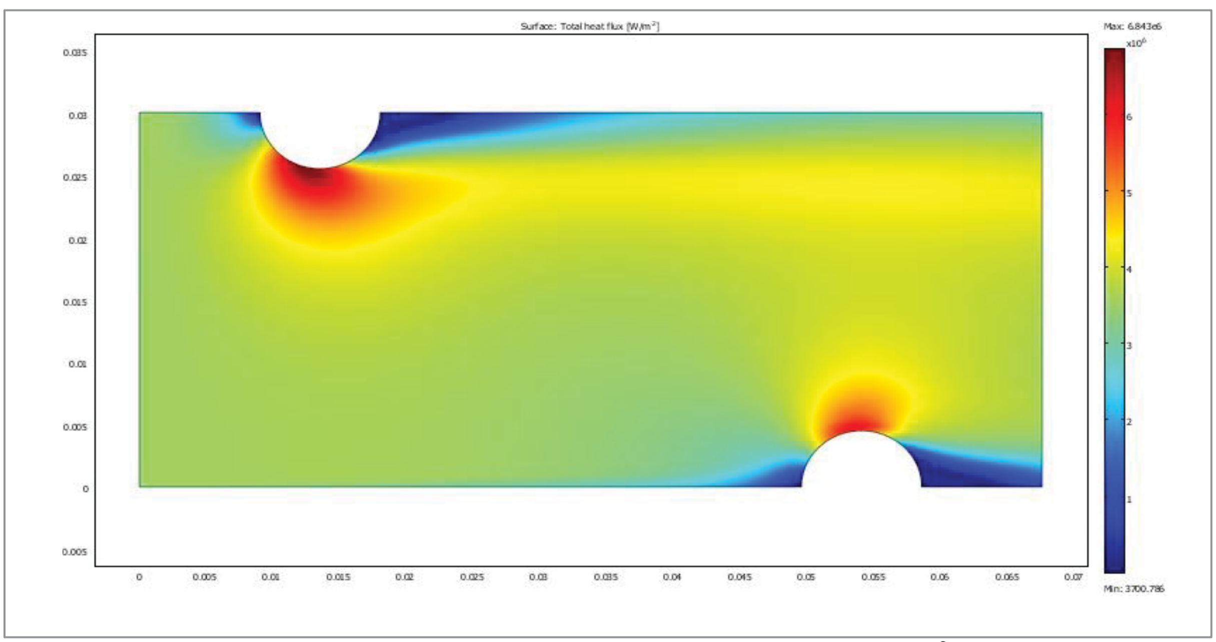


Figure 6-11: Heat flux distribution (units are in W/m^2)

6.5 Parameter Selection for the Optimizer Component

The efficiency of EAs and convergence rate is closely related to the search control parameters such as population size, crossover probability and mutation probability. Several research studies have been conducted to evaluate the effect of the control parameters on different problem scenarios. Some suggested values can be found in literature (e.g., Grefenstette, 1986; Schaffer et al., 1989); however, ultimately, the values of the control parameters are problem-specific.

Table 6-6 lists suggested MOEA control parameters; these parameters are varied in a pilot study to study the effect on convergence rate with respect to the design decision problem considered in this research investigation.

Table 6-6: MOEA (NSGA-II) Control parameters

MOEA Parameters	Parameter Values
Population Size	*Pop*
Maximum Generations	Gen_{max}
Reproduction / Selection	Tournament Selection (Rank & crowding distance)
Crossover Probability	*c*
Mutation Probability	*m*

The remainder of this section discusses the settings of control parameters for NSGA II. The selection of control parameters is based on pilot experiments performed on maximum number of objectives and design variables (three objectives and six design variables). The main reason for conducting pilot study on maximum number of objective functions and design variables is the increase in objectives and design variables leads to rapid growth of the solution search space and makes it difficult to find non-dominated solutions close to the Pareto front

(Reed et al., 2000; Praditwong and Xin Yao, 2007). Thus, the selection of control parameters based on worst case scenario is necessary.

The population size, *Pop*, is the number of candidate design solutions evaluated at each generation (i.e., iteration). Population size used in an EA depends on a number of factors related to the number of decision variables, the complexity of the problem, etc. An MOEA population cannot be sized according to the desired number of nondominated solutions in a problem. A small population size can limit the capability of exploration of the search space and inhibits the purpose of crossover operations. Conversely, use of large population size can be computationally-expensive. Thus, the selection of population size is an important step and greatly depends on the problem type and structure. The maximum number of generations, $Gen_{\max}$, denotes the number of generations (i.e., iterations) performed and indicates when to terminate the search and report the best set of design solutions so far. The main criterion is to recognize that the search has converged.

The Reproduction/Selection operator cannot create new solution in the population; it only selects and makes copies of good solution to keep population size constant. In EAs, the creation of new solution is carried out by Crossover operator. The crossover probability, *c*, defines how often crossover is performed. The crossover probability rate varies based on problem type, but should be high enough to encourage mixing. A low crossover probability decreases the speed of convergence due to lower search intensification rate. On the other hand, a high crossover probability may contribute to premature convergence. In general, the recommended range of *c* is between 0.60 and 0.95 (Grefenstette, 1986). Likewise, the Mutation probability, *m*, denotes how often parts of a solution undergoes random perturbations. It introduces diversity into the population and should be a small value to avoid the algorithm from becoming effectively a random search. In general, the recommended range of *m* is between 0 and 0.20 (Schaffer et al., 1989). In the following section the results of pilot study along with brief description of selection of control parameters for Optimizer based on pilot study findings is presented.

6.6 Parameter Setting for the Optimization Procedure

In this section, the impact of optimization procedure control parameters on the convergence performance of the optimization procedure is empirically investigated. Hence, a pilot study is conducted to determine best control parameter values for the Optimizer component, utilizing a multiobjective optimization evolutionary algorithm (MOEA). Specifically, the Optimizer component uses NSGA II developed by Deb et al. (2002). The control parameters include: (1) the population size Pop, (2) the maximum number of generations Genmax, (3) the crossover probability c, and (4) the mutation probability m.

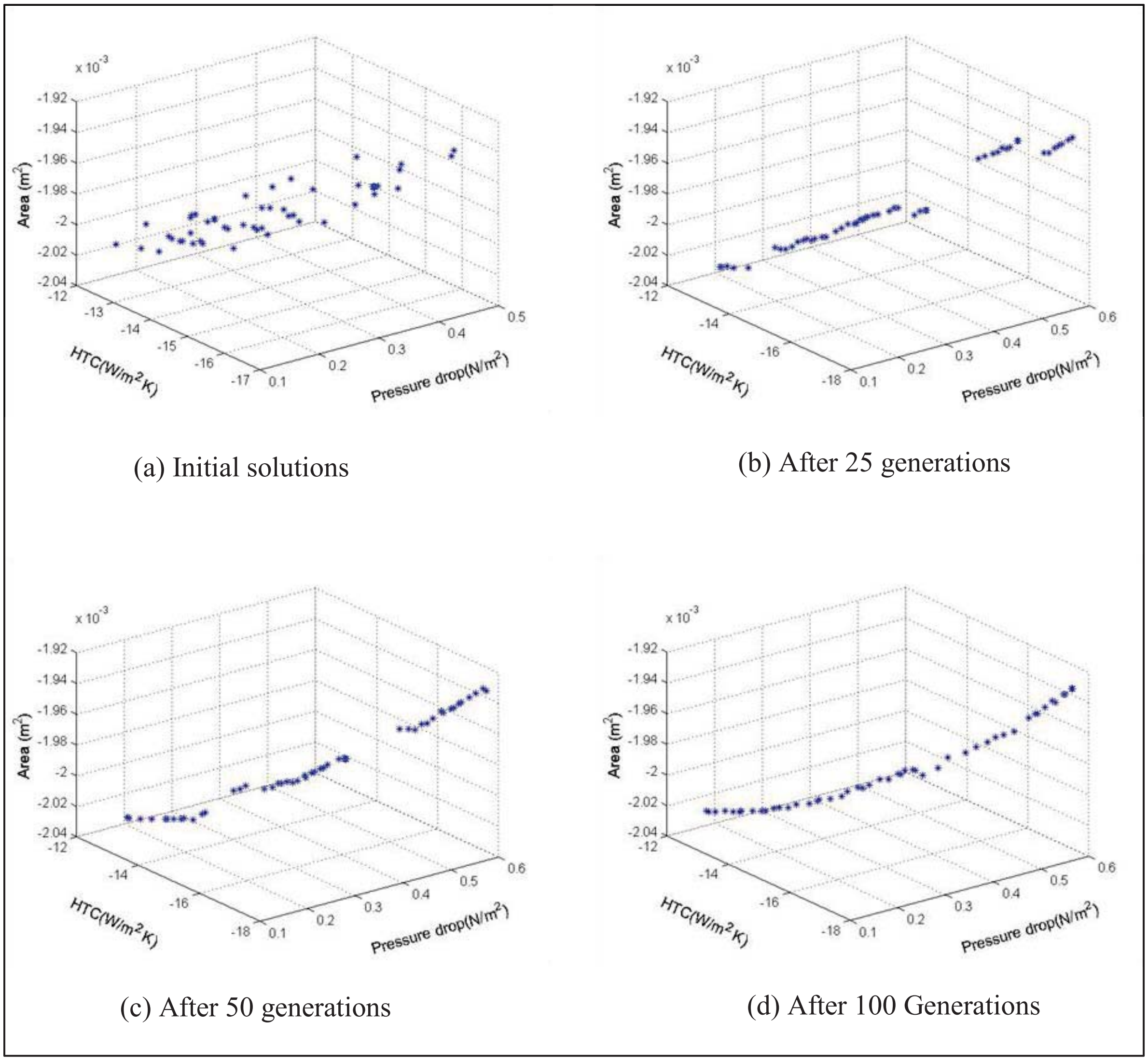
The influence of parameters on the convergence behavior is studied by selecting range of parameters as shown in Table 6-7. The range of values of the control parameters given in Table 6-7 results in 18 different combinations. The results of the parameter value combination with the best convergence performance are given (Figure 6-12 (a) through (d)); however, the complete results from the pilot study can be found in APPENDIX A. The set of control parameter values used for the computational study are identified from pilot study (Table 6-7) and the best control parameters found for this specific design problem are listed in Table 6-8.

Table 6-7: Range of parameters for pilot study

Control Parameter	Values
Population (*Pop*)	{10, 25,50}
Generations (Gen_{max})	{100}
Crossover Probability (*c*)	{80%, 90%, 95%}
Mutation Probability (*m*)	{5%, 10%}
Total Number of Pilot Runs	18

Table 6-8: Parameters identified from pilot study

Population size (*Pop*) = 50	Generations (Gen_{max}) =100
Crossover (*c*) = 90%	Mutation Probability (*m*) = 10%



(a) Initial solutions

(b) After 25 generations

(c) After 50 generations

(d) After 100 Generations

Figure 6-12: Pilot study of three objective and six design variables (*c*=90% & *m*=10%)

The next two chapters summarize the computational study of the performance of the proposed multiobjective design optimization framework. CHAPTER 7: begins with optimizing cooling channel design under a single objective followed by the optimization of the internal cooling channel design in the presence of two objectives. In CHAPTER 8:, the optimization is expanded to three design objectives, which has not been attempted in the current research literature.

CHAPTER 7:
COMPUTATIONAL STUDY: COOLING CHANNEL OPTIMIZATION WITH ONE AND TWO DESIGN OBJECTIVES

7.1 Introduction

The current chapter and CHAPTER 8 summarize experimental results from the computational study. This chapter begins with a brief review of literature on traditional and non-traditional approach in design optimization of gas turbine blade cooling channel. This literature review shows the merits of this multiobjective optimization framework compared to other methods. Then, it presents the first set of single objective and two objective optimization results. The last set of experimental results addressing three objective functions are presented in CHAPTER 8. All optimization experiments are performed using the best problem-specific control parameters (Pop = 50, $Gen_{\max}$ =100, crossover probability c = 90% and mutation probability m=10%) identified through pilot study. The combination of 50 population and 100 generations resulted in 5,000 design evaluations in one single optimization run.

7.2 Conventional Design Optimization: Cooling Channel Design

In the beginning, gas turbine manufacturers relied primarily on a "build and bust" approach in the design of hot gas path components. Initially the prototypes of parts are designed based on empirical correlations for aerodynamics and heat transfer, along with performance data from previous models of gas turbine engines. During that period and even now, the laboratory experiments are extremely complex and expensive to conduct for realistic engine conditions. Instead, the prototype engine is built and tested until failure, a process which is costly and time-consuming. It is also largely unknown or difficult to pinpoint a parameter or part that contributes to a failure of gas turbine. These difficulties gave rise to numerical and experimental methods to streamline the design process and are now known to be traditional methods in the design optimization process.

At present, the design and optimization of most mechanical components starts with a traditional approach of using numerical simulation methods to identify the best set of design variable values. Only the selected set of these design variables are validated using experimental methods. The high cost, high labor and amount of time required to conduct experiments makes it almost impossible to use as a primary tool for design optimization process. Due to the above shortcomings, the experimental methods are only used in validating set of designs, which are proved to be the best designs either by numerical methods or empirical methods.

7.2.1 Numerical Simulation Methods: Cooling Channel Design

Heat transfer and fluid flow predictions in ribbed channels using numerical simulation methods has been an active research area for several decades and a vast amount of research has been published in this area. Typically, numerical methods such as CFD in conjunction with heat transfer simulation capabilities are used in the optimization of rib configuration in gas turbine blade cooling channels. The process of simulation of heat transfer between solid and fluid phase is also referred as conjugate heat transfer (CHT). One of the first CHT numerical simulations of a cooled turbine airfoil is the work of Bohn et al. (1995). The authors create a computational model of a two-dimensional cooling channel of a guide vane and predict the external surface temperature within 2% of an experimental value using some in-house code. The conjugate numerical model of the guide vane is extended to three-dimensions by Bohn and Schonenborn (1996). A significant advance in the computational capability during the 1990's is the development of robust commercial numerical simulation codes. Application of numerical techniques to optimize gas turbine blade internal cooling design has attracted many researchers in recent years. They use commercial numerical simulation codes such as FLUENT, STAR-CD, ANSYS and COMSOL for internal cooling channel simulation (e.g., Liou et al., 1991; Prakash and Zerkle, 1995; Bredberg and Davidson, 1999; Chen et al., 2001; Acharya and Saha, 2005; Keshmiri, 2012).

The main drawback of optimization by numerical simulation is amount of human interactivity required, in that, for each new design a new set of design variables are manually entered and then evaluated via simulation. To overcome this drawback, one can automate the process to run simulations for range of design variables. However, the designs simulated are targeted to satisfy only one objective function and are unidirectional. The designs in this case are not evolved to discover a set of optimized designs. Instead, one has to spend considerable time evaluating a pool of candidate designs.

7.2.2 Experimental Methods: Cooling Channel Design

Under the traditional design optimization methods, the study of numerous candidate designs of gas turbine internal cooling channels by experimental methods is cost prohibitive. Figure 7-1 shows a simple typical wind tunnel test facility to measure the performance (heat transfer rate and pressure drop) for rib arrangements in the test section. Wind tunnels are equipped to circulate atmospheric air and measure its flow and heat transfer parameters in closed- or open-loop tunnel. The experimental setup in Figure 7-1 is an open-loop wind tunnel where the air is exhausted into the atmosphere.

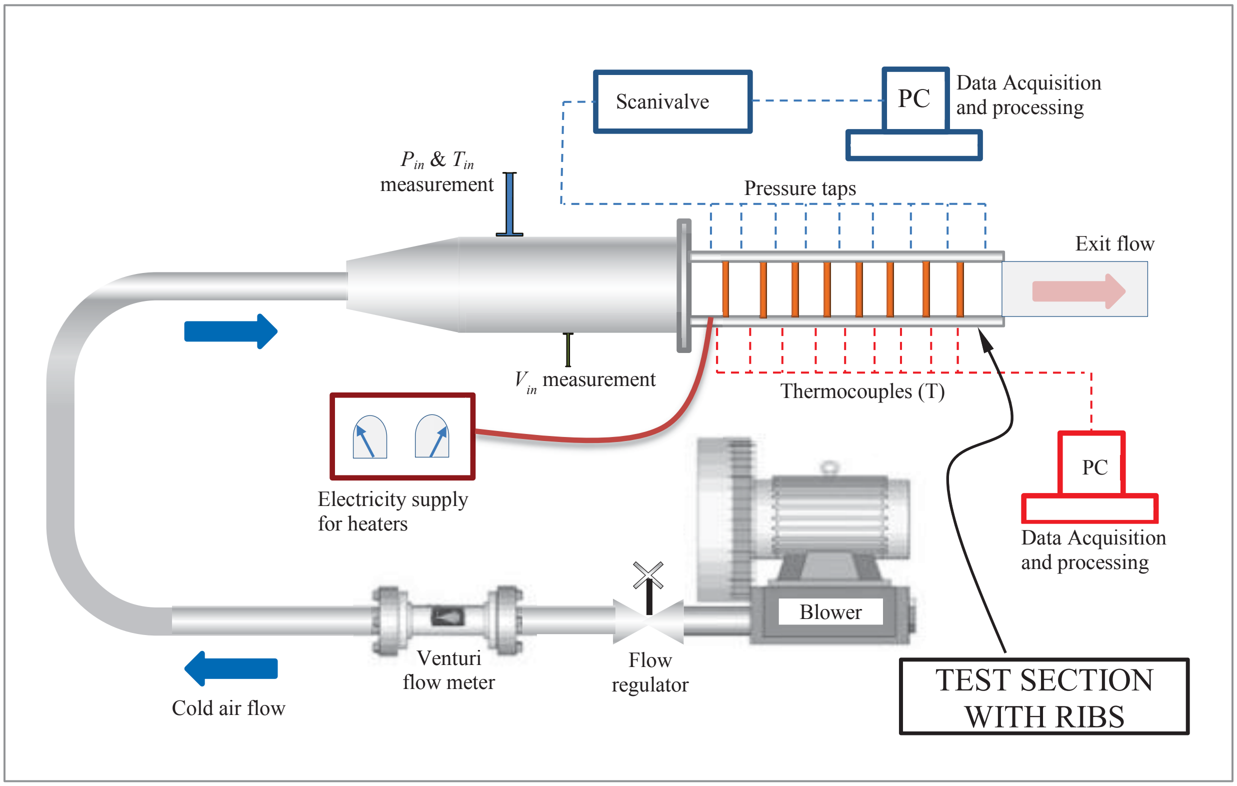


Figure 7-1: A typical wind tunnel experimental set up for cooling channel design

The test section in the experimental setup is a critical part of the traditional design optimization process of gas turbine blades. This section is designed and built in such a way that it can be easily removed and replaced with different design specifications. In cooling channel design experimentation, the test section is constructed with electrical resistive type foil-heated channel and ribs are made from copper or brass and are attached to the heated foils (Han et al., 2000). The test section mimics the scaled-down environment of blade cooling channel (i.e., temperature, pressure and velocities of flow are scaled down). The cooling air from atmosphere is passed through test section (cooling channel) to facilitate heat transfer from heated ribs and surface of cooling channel. The flow and heat transfer parameters such as velocity, pressure, temperature at the test section are measured using instruments such as pitot-tubes, pressure taps, and thermocouples. The measured parameters are used to calculate the heat transfer rate and pressure drop to determine the efficacy of the design. To test the performance of next design the entire test section is removed and replaced with new set of ribs incorporating new design specifications. Sometimes this process may take days before the next design is tested. And it is also common that experiments provide ideal conditions, and measured data may need some extrapolation before they can be applied to real design. Therefore experimental method is best suited for validation purpose once the designer has a handful of optimal design in hand.

Many researchers used wind tunnel experiments for gas turbine blade cooling channel designs. More comprehensive details on process and procedures are described in number of books (e.g., Han et al., 2000; Boyce, 2006) and research papers (e.g., Wagner et al., 1991; Zhang et al., 1995; Parsons et al., 1995; Tse and Steuber, 1996; Azad et al., 2002; Han et al., 2011). Readers are advised to refer to them for more information on experimental methods.

7.3 Non-Conventional Design Optimization: Cooling Channel Design

This section revisits literature review and presents again a brief review of a non-conventional approach applied to blade cooling channel design optimization. Due to the complex nature of the design problem, only few researchers so far have attempted to optimize blade cooling channel.

The optimization of cooling channel is studied extensively by Kim and Kim (2002), who consider the optimization of internal cooling channels with straight rectangular ribs (Kim and

Kim, 2004a), angled ribs (Kim and Kim, 2004b) and the V-shaped ribs (Kim and Lee, 2007b). They identify the values of geometric design variables with the objective function defined as a linear function of heat transfer coefficient and friction drag coefficient (a surrogate measure for pressure drop). The two objectives considered in their study are heat transfer coefficient and coolant flow pressure drop. However, these two objectives are combined to form a single composite function using a vector of subjective weights and solved using a response surface-based optimization method. The best values of design variables are obtained with variation of the weighting factor. The selection of the weights is based on the designer's experience, which could lead to errors in optimization if the weights are not carefully selected. Kim and Kim (2002) group also study one other approach to solve multiobjective optimization problem, where they solve each objective functions as a single objective optimization problem, and later, the best solutions of all objectives are mapped to find non-dominated solutions. This approach does not consider the objective functions simultaneously and independently in the problem. In addition, it is proved that their proposed method is laborious and can be time-consuming.

To overcome the limitations of weighted sum approach, Roy et al. (2002) attempt to optimize a turbine blade cooling system design, where their study mainly focuses on handling the presence of complex inseparable function interaction among its decision variables. They propose an evolutionary-based multiobjective optimization algorithm called Generalized Regression Genetic Algorithm (GRGA). Their study shows that GRGA successfully handles complex inseparable function interaction and gives a range of feasible designs. The authors consider only two objectives for optimization – minimization of coolant mass flow rate and minimization of the blade metal temperature. Also, it is not clear that the study simultaneously considers both the objectives for optimization. No researchers have performed multiobjective optimization using more than two objectives simultaneously.

One can notice that the problems are converted to minimization problems, even though there are two objectives (h) and (A) which are to be maximized. In general, many optimization algorithms are developed to solve only one type of optimization problem, i.e., either minimization or maximization. The second generation of NSGA is used in this research to solve the minimization problems. To solve the maximization problem, the duality principle (Rao, 1984) is applied, i.e., problem is converted to minimization by multiplying objective function by -1. The duality principle enables the use of conflicting objectives where some need to be maximized and some are to be minimized. Hence, the objective functions heat transfer coefficient (h) and Area (A) are multiplied by -1 to convert this problem to minimization.

7.4 Single-Objective Function Optimization

The goal in single objective optimization is to converge to the (global) optimum. Single-objective problems either minimize or maximize the objective function value depending upon the problem type attempting to reach single optimum value. In cooling channel design optimization, the heat transfer coefficient (h) is selected as an objective function because of its importance in blade cooling. The objective here is to maximize the value of h varying design variable values. The next three sections present results of optimization of h for 2, 4 and 6 design variables. The optimization process is performed using the control parameters (Pop = 50, Gen_{max} = 100, c = 90% and m = 10%) identified via a pilot study.

7.4.1 Case 1: Two Design Variables

For Case 1, radii R_1 and R_2 (i.e., radii of Ribs 1 and 2, respectively) are considered as design variables (Figure 7-2). The radii values of the ribs are varied between 1mm to 5.5mm to find optimal objective function (h) value.

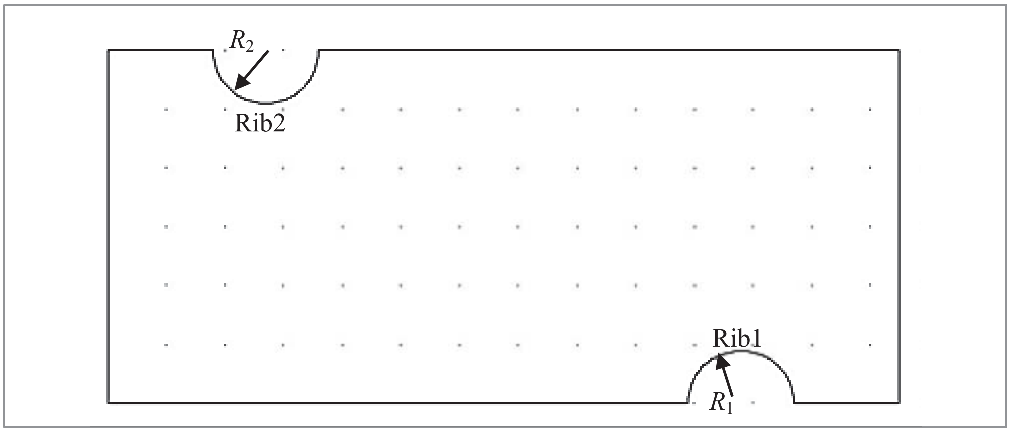


Figure 7-2: Cooling channel with design variables R_1 and R_2

Figure 7-3 shows graphical representation of single-objective optimization results. The y-axis represents objective function, heat transfer coefficient (h), which needs to be maximized, whereas the x-axis represents number of generations (Gen_{max}). The objective function (h) value at each generation is average of 50 objective function values (Pop) in that generation and it is compared with highest value of h in the same generation (Figure 7-3). It is observed that the convergence of objective function h to global optimal value is linear and rapidly converge within the first few generations (5 generations). In other words, the convergence rate slows and remains almost constant after 5th generation. To save computational time, one could stop the optimization process just after the 5th generation and report results. The best value of h found in this case is 15.4253 W/m^2.K (over an average of 50 design specifications in the population). Similarly, the initial h value is 13.3949 W/m^2 K (over an average of 50 design specifications in the population).

As a result, a 15.15% increase in heat transfer coefficient or cooling effectiveness (directly proportional to HTC) is achieved.

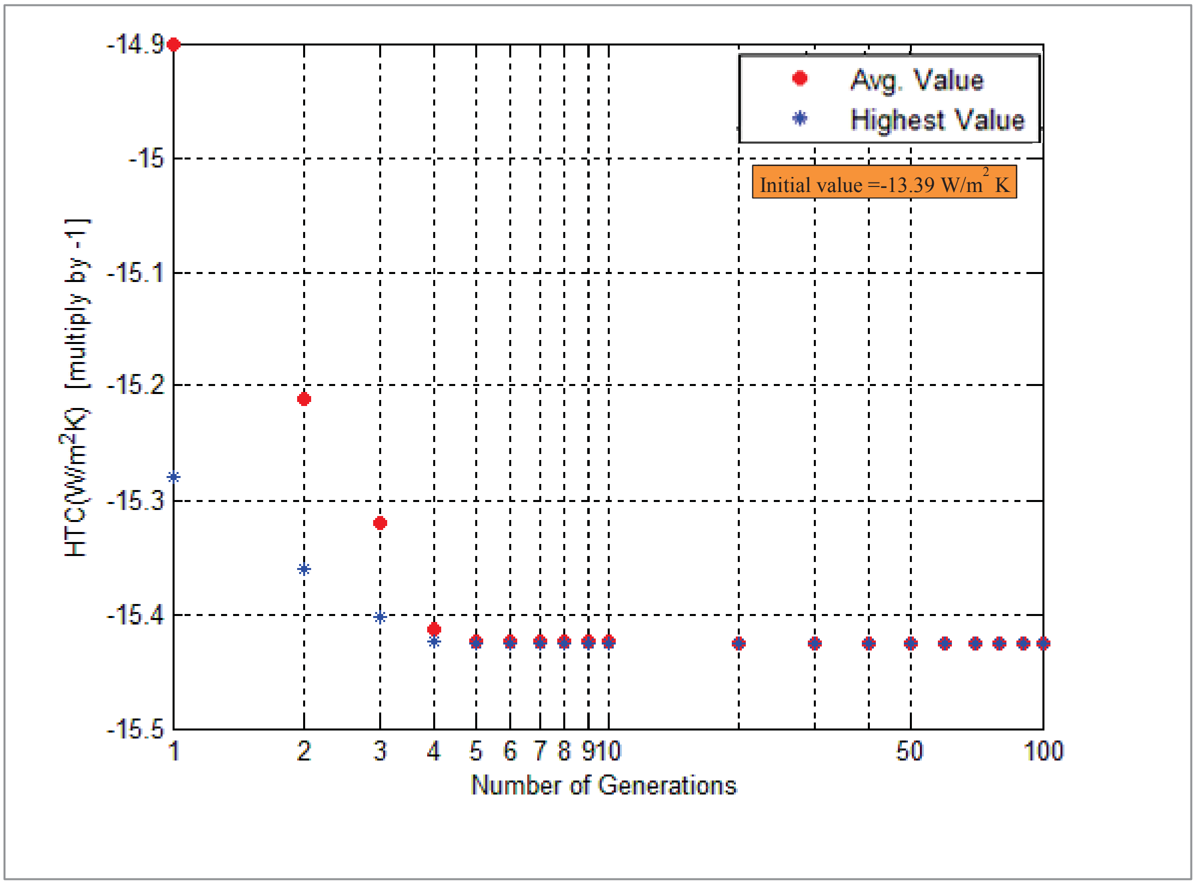


Figure 7-3: Convergence behavior for single objective and two design variables

7.4.2 Case 2: Four Design Variables

For Case 2, radii R_1, R_2 (i.e., radii of Ribs 1 and 2, respectively) and fillets radii R_3, and R_4 are considered as design variables (Figure 7-4). The radii of the ribs are varied between 1mm to 5.5mm and fillets radii are varied between 0.1mm to 0.4mm. The fillets created at the intersection of ribs with top and bottom walls facilitate the smooth flow of coolant without creating a stagnation point. A stagnation point leads to pressure build-up and a lower heat transfer coefficient. Hence, the effect of the Rib 1 fillets radii R_3, R_4 (Figure 7-4) and the Rib 2 fillet radii R_5 and R_6 (Figure 7-6) are important and should be optimized and included in the design specification.

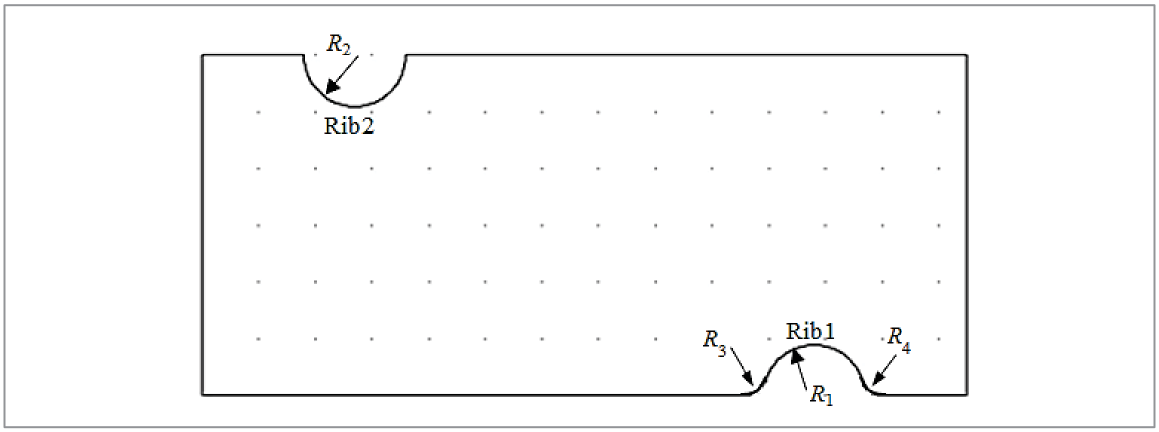


Figure 7-4: Cooling channel with design variables R_1, R_2, R_3 and R_4

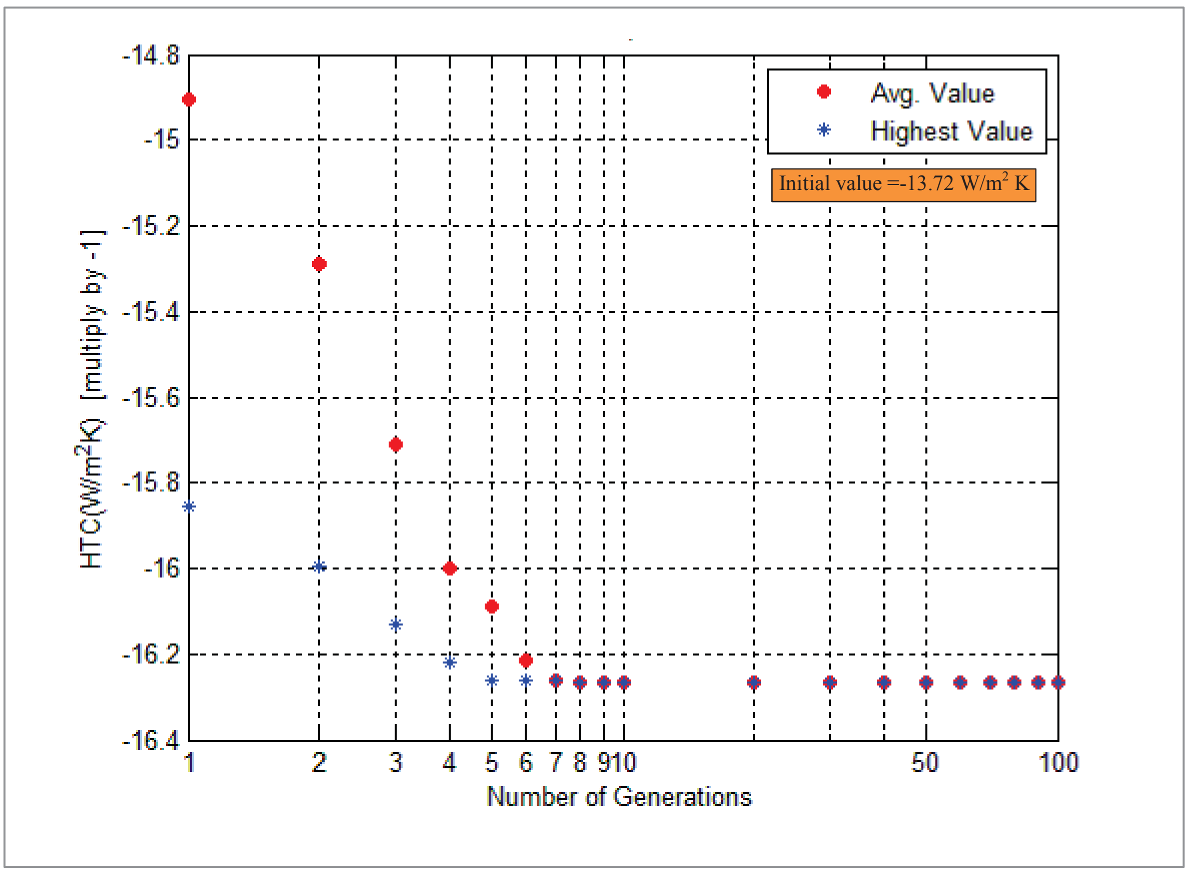


Figure 7-5: Convergence behavior for single objective and four design variables

From Figure 7-5, it is evident that the convergence rate in the case of four design variables is slow and appears to take more generations than the two design variable problem discussed in Section 7.4.1. The average global optimal value of h found in this case is 16.2793 $W/m^2.K$ (over an average of 50 design specifications in the population). Similarly, the average initial h value is 13.7239 W/m^2K (over an average of 50 design specifications in the population). A 18.62% increase in the heat transfer coefficient is achieved. By introducing the fillet radii as design variables, the four design variable problem resulted in 5.53% more cooling effectiveness than two design variable problem.

7.4.3 Case 3: Six Design Variables

For Case 3, radii R_1, R_2 (i.e., radii of Ribs 1 and 2, respectively) and fillets radii R_3, R_4, R_5, and R_6, are the complete set of design variables (Figure 7-6). Again the radii of ribs are varied between 1mm to 5.5mm and fillets radii are varied between 0.1mm to 0.4mm.

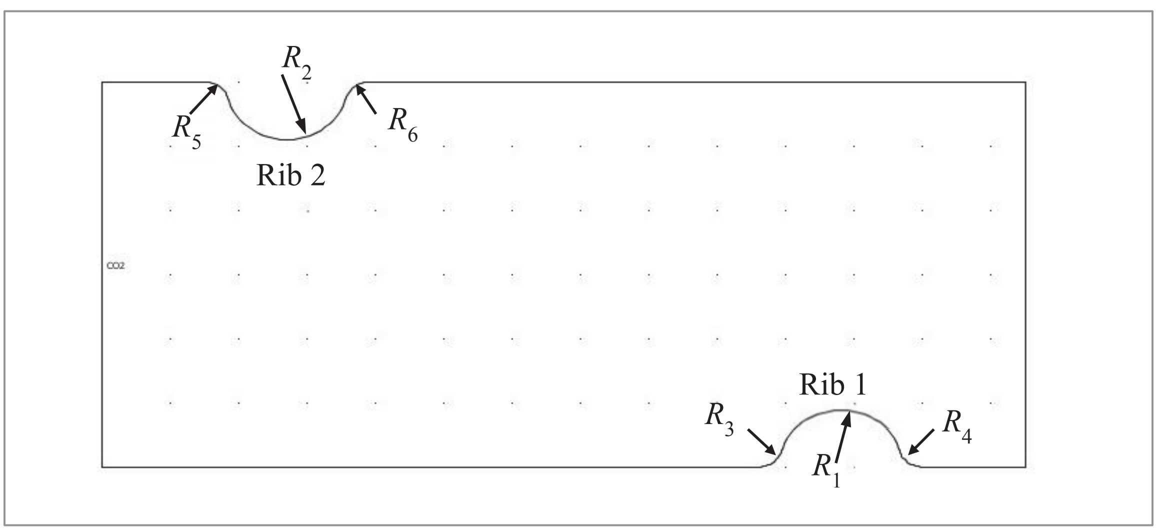


Figure 7-6: Cooling channel with design variables R_1, R_2, R_3, R_4, R_5, and R_6

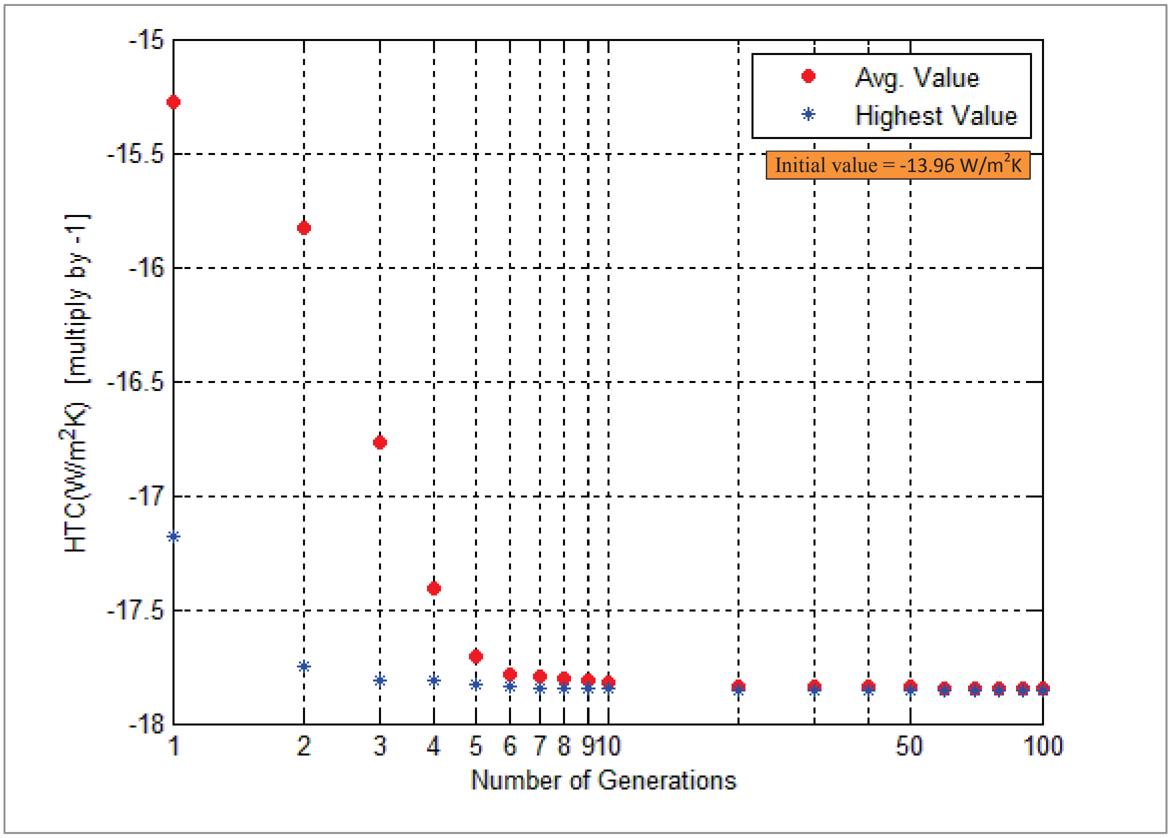


Figure 7-7: Convergence behavior for single objective and six design variable optimization

From Figure 7-7, again it is evident that the convergence rate in case of six design variables further slows down compared to both the four and two design variable problem. The average global optimal value of h found in this case is 17.8476 W/m^2.K (over an average of 50 design specifications in the population). Similarly, the average initial h value is 13.9687 W/m^{2}K (over an average of 50 design specifications in the population). An average a 27.75% increase in heat transfer coefficient is achieved. By introducing the additional fillet radii as design variables, the six design variable problem results in 15.70% more cooling effectiveness than the two design variable problem and 9.63% more cooling effectiveness than the four design variable problem.

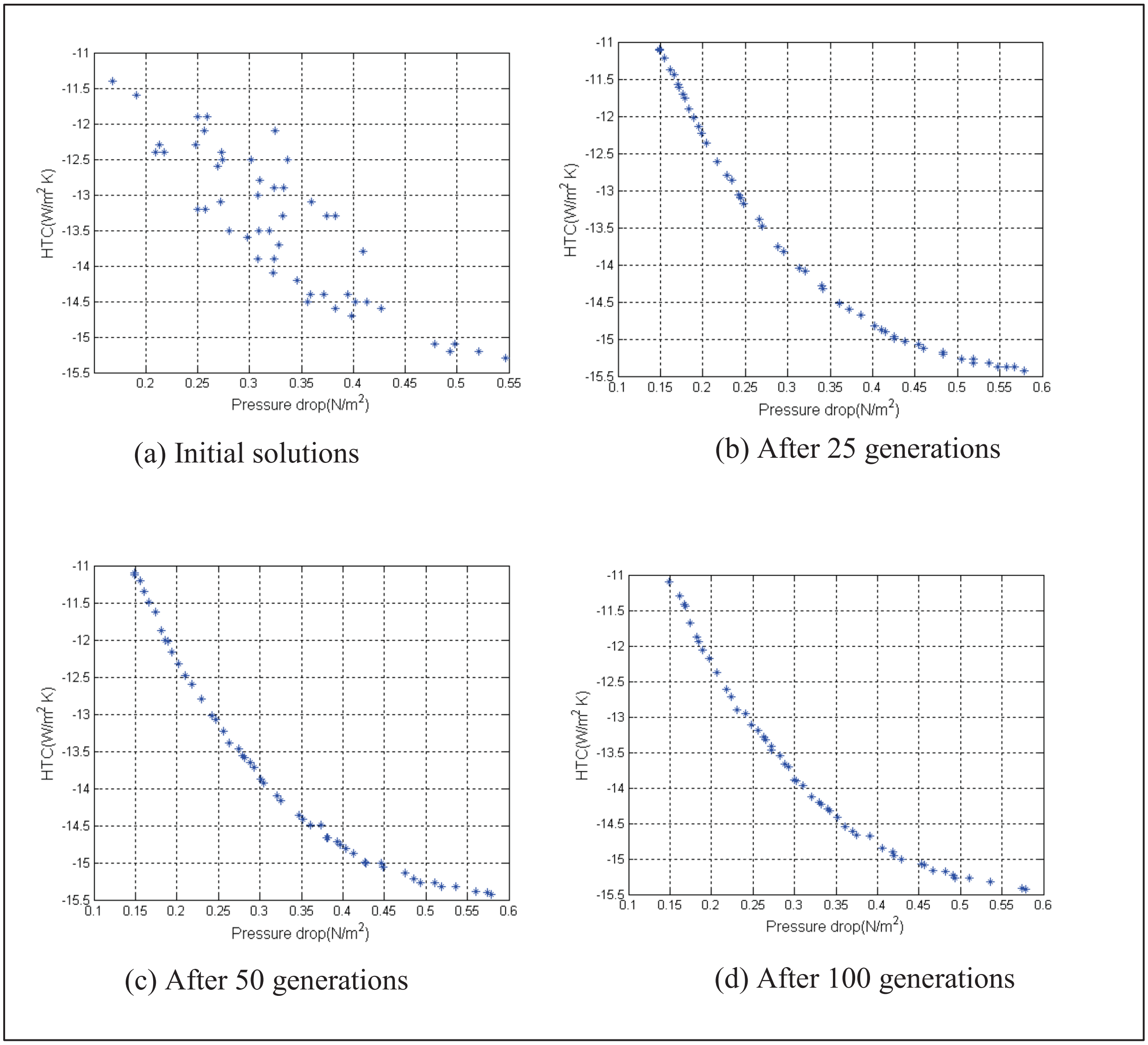
7.5 Two-Objective Functions Optimization

In the single-objective optimization problem, it is seen that the solution converges to one solution. Therefore, one can easily chose the final design specifications to use without ambiguity. But, when more than one objective functions are considered simultaneously for optimization and a Pareto-based optimization approach as proposed in this research, there exists a number of trade-off, or compromise, solutions. Without any further information, no solution from the set of compromise solutions can be said to be better than any other in the set. Thus, in multiobjective optimization, an effort must be made in finding the set of trade-off optimal solutions by considering all objectives to be equally important. Thus, it can be conjectured that there are two goals in a multiobjective optimization. First, set of solutions that is as close to the Pareto-optimal front as possible must be identified. Second, the set of solutions must be as diverse as possible. After a set of such trade-off solutions are found, a user can then use higher-level preference information to make a choice. The above such trade-off solutions are obtained a multiobjective optimization involves two search spaces instead of one. In single-objective optimization, there is only one search space – the decision variable space. However, in multiobjective optimization, there exists an associated space called objective, or criteria, space.

This section presents results of cooling channel design considering two objectives – heat transfer coefficient (h) and coolant pressure drop (Δp). The experiments are performed with same set of evolutionary algorithm control parameters used in the single-objective optimization discussed in Section 7.4 (i.e., Pop = 50, $Gen_{\max}$ = 100, c = 90% and m = 10%). The next three sub sections present results of optimization of h and Δp, for 2, 4 and 6 design variables. The objective here is to maximize the value of h and minimize the value of Δp varying design variable values.

7.5.1 Case 1: Two Design Variables

For Case 1, radii R_1 and R_2 (i.e., radii of Ribs 1 and 2, respectively) are considered as design variables (see Figure 7-2). The radii of these variables are varied between 1mm to 5.5mm. Figure 7-8 shows the graphical representation of multiobjective optimization results. The y-axis represents the objective function heat transfer coefficient (h), which is to be maximized. The x-axis represents the objective function coolant pressure drop (Δp), which is to be minimized. Figure 7-8 (a) shows initial set of objective function values before being optimized. Figure 7-8 (b), (c) and (d), show solutions progressing towards Pareto optimal (efficiency) front after 25, 50 and 100 generations, respectively. For illustration purposes, in Figure 7-9 three solution values and corresponding design specifications and are used to build three designs of cooling channel as shown in Figure 7-9. Design 1 has smaller rib radii resulting in a low pressure drop $\Delta p = 0.1485$ N/m^2 and a low heat transfer coefficient $h = 11.09$ W/m^{2}K. Similarly, Design 3 with larger ribs results in high pressure drop (0.578 N/m^2) and high heat transfer coefficient (15.42 W/m^{2}K). Design 2 is selected from the mid-section of the Pareto front and it results in a moderate h (13.82 W/m^{2}K) and pressure drop (0.2955N/m^2).



(a) Initial solutions

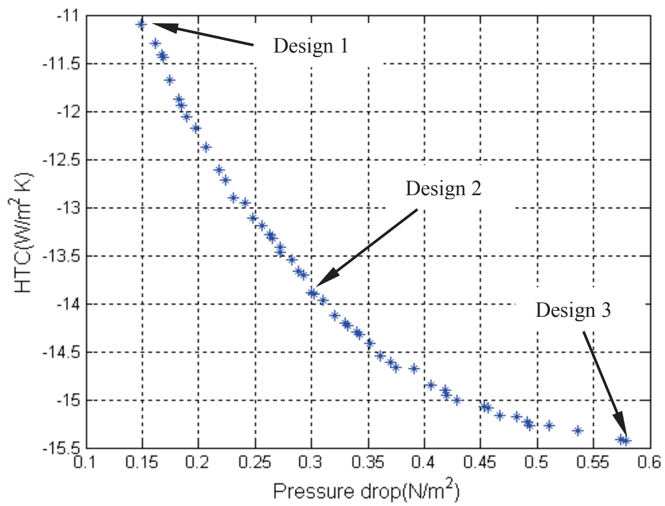
(b) After 25 generations

(c) After 50 generations

(d) After 100 generations

Figure 7-8: Pareto optimal front considering two objective and two design variables

	Design 1	Design 2	Design 3
R1	0.001	0.001218	0.005493
R2	0.001	0.00437	0.0055
Δp	0.1485	0.2955	0.5783
h	-11.09	-13.82	-15.42



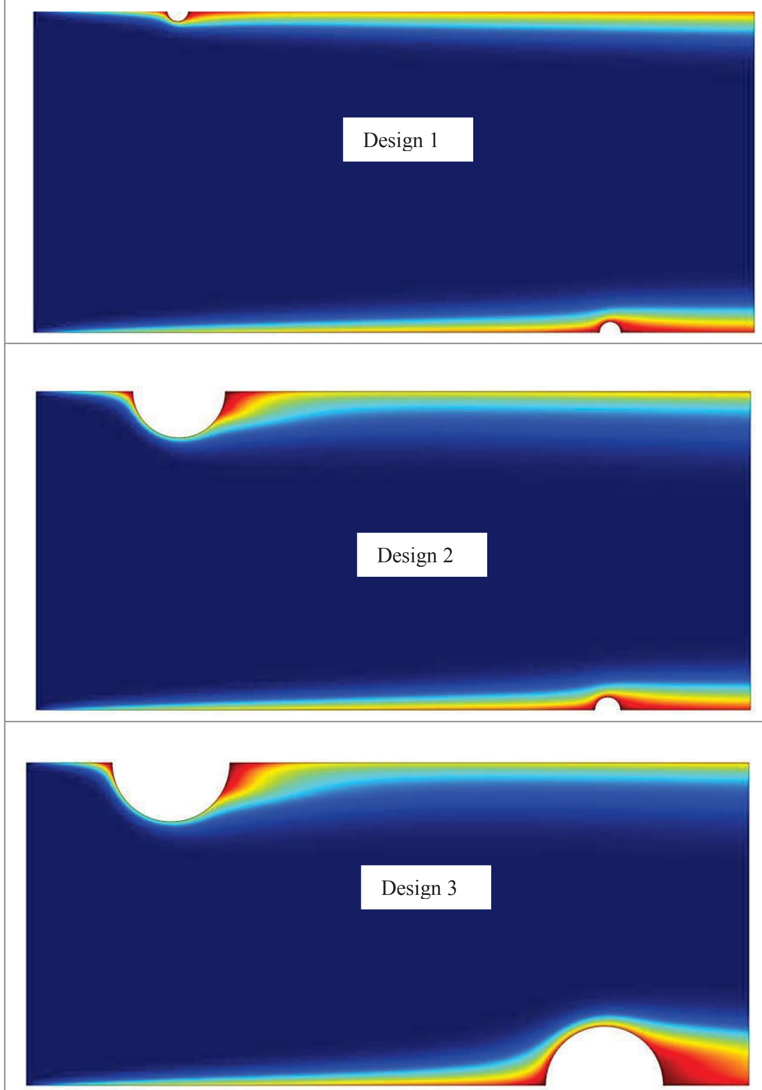


Figure 7-9: Design specifications of cooling channel for three selected optimal solutions

7.5.2 Case 2: Four Design Variables

For Case 2, radii R_1, R_2 (i.e., radii of Ribs 1 and 2, respectively) and fillets radii R_3, and R_4 are considered as design variables (Figure 7-4). The radii of ribs are varied between 1mm to 5.5mm and fillets radii are varied between 0.1mm to 0.4mm.

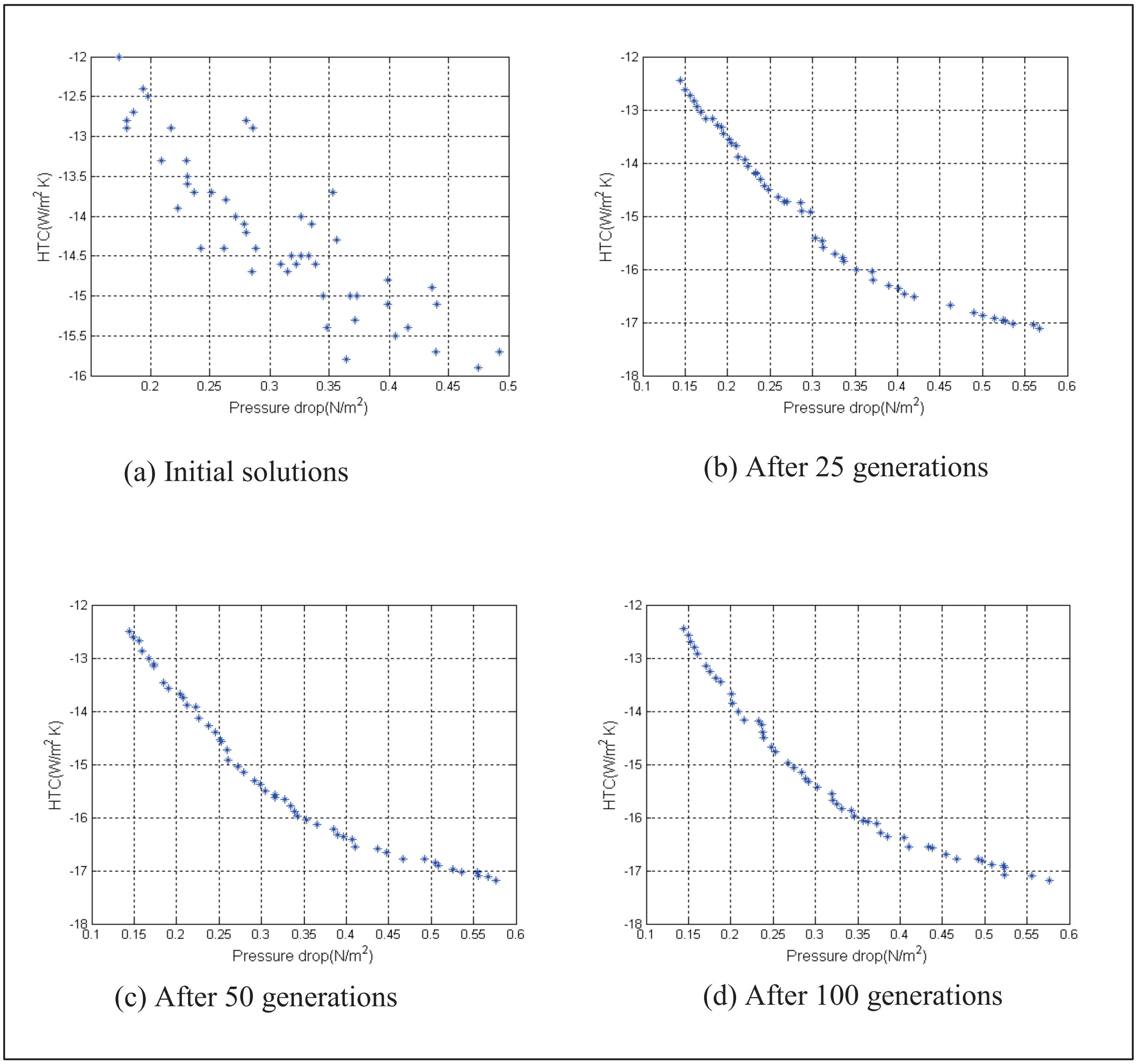
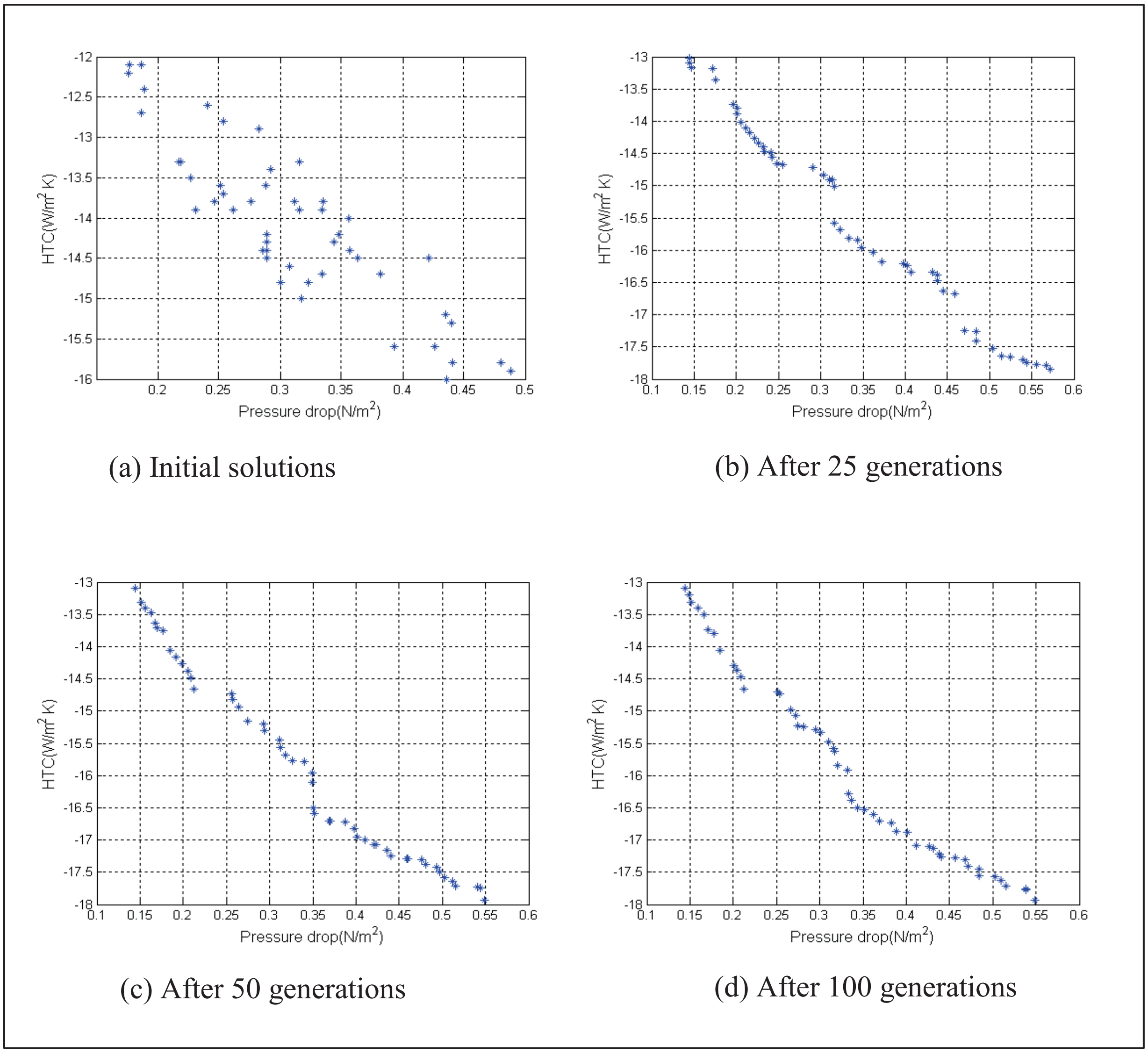


Figure 7-10: Pareto optimal front considering two objectives and four design variables

The Pareto optimal solution set each for the two objectives and the four design variables (Figure 7-10) suggest that the solutions are not converging to a smooth and uniform Pareto front as shown in the two variable case. This is because the solution space of the problem increases exponentially with the increase in the number of decision variables. Therefore, more search iterations (i.e., generations) with efficient search strategy (i.e., fine-tuning the search control parameters such as crossover *c* and mutation *m*) is required to explore more promising regions.

7.5.3 Case 3: Six Design Variables

For Case 3, radii R_1, R_2 (i.e., radii of Ribs 1 and 2, respectively) and fillets radii R_3, R_4, R_5, and R_6, complete set of design variables (Figure 7-6). The radii of ribs are varied between 1mm to 5.5mm and fillets radii are varied between 0.1mm to 0.4mm.



(a) Initial solutions

(b) After 25 generations

(c) After 50 generations

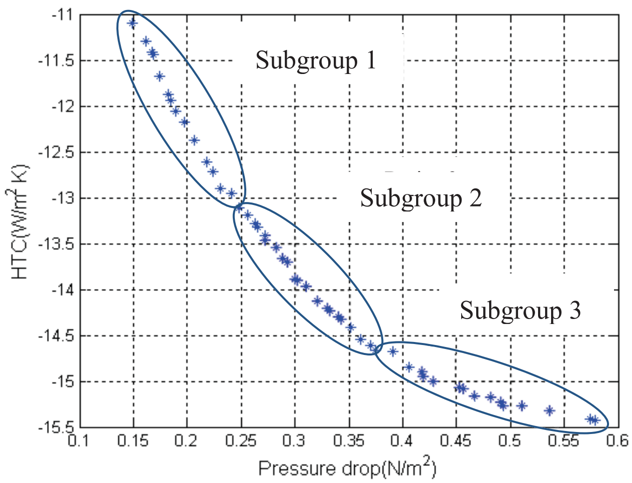
(d) After 100 generations

Figure 7-11: Pareto optimal front considering two objectives and six design variables

The Pareto front for 2 objectives and 6 design variables (Figure 7-11) further suggests that the increase in design variables decreases the progression of solution towards Pareto optimal front. As mentioned in previous section, an increase in the number of design variables causes the solution space of the problem to increase exponentially and requires more search iterations with right control parameters values.

7.6 Reducing the Size of the Non-Dominated Set: Clustering

One of the uses of generating the Pareto optimal frontier is faster decision-making in the selection of a solution in the presence of more than one objective. This selection process is further enhanced by applying clustering technique (Zitzler, 1999) to the set of Pareto optima. In this technique, each of *N* solutions is assumed to belong to a separate cluster. The distances between all pairs of clusters are found by calculating Euclidean distance formed by imaginary cuboid formed around centroid of each cluster. Two clusters having a minimum distance between them are merged together into a bigger cluster. This procedure is continued until the desired numbers of clusters are identified. In this research investigation it is appropriate to divide Pareto optimal front solution to only three subgroups (clusters) to accommodate three design types from which a designer can select the most preferred. For illustration of this technique, suppose that three types of designs are proposed (Figure 7-12). Subgroup 1 (cluster) contains the Pareto optimal solutions that satisfy objective function minimization of *pressure drop* (Δp) better than any other solutions in Subgroup 2 and 3. Similarly, Subgroup 3 better satisfies the maximization of objective function h better than any other Pareto optimal solutions in the Subgroups 1 and 2. The Pareto optimal solutions in Subgroup 2 fall in between Subgroups 1 and 3 with moderate optimization of both objective functions. Thus, clustering provides visual insight of solutions and aids the decision- maker in selecting a solution. Although it is not within the scope of this research investigation, further research is necessary to explore the best approach to select the most preferred solution from a set Pareto optima.



Subgroup 1:
Designs in this group satisfy in minimizing objective function (Δp) at the expense of other objective function (h)

Subgroup 2:
Designs in this group moderately satisfy both Objective functions (Δp) and (h)

Subgroup 3:
Designs in this group satisfy maximizing Objective function (h) at the expense of other objective function (Δp)

Figure 7-12: Pareto optimal front divided into three clusters of solutions.

CHAPTER 8:
COMPUTATIONAL STUDY: COOLING CHANNEL OPTIMIZATION WITH THREE DESIGN OBJECTIVES

8.1 Introduction

The main objective of this research is to build a multiobjective design optimization for mechanical component design, specifically gas turbine blade internal cooling channels. The proposed optimization framework is successfully built by integrating multiobjective evolutionary algorithms and computational fluid dynamics numerical simulation. In CHAPTER 7, Section 4 and Section 5 introduced first set of single objective and two objective optimization results. In this current chapter the results with the introduction of third objective function Area (A) to minimize the material consumption by maximizing the cavity area inside the cooling channel is presented. Experimental runs are performed as usual for two, four and six design variables with optimal parameters identified in CHAPTER 6.

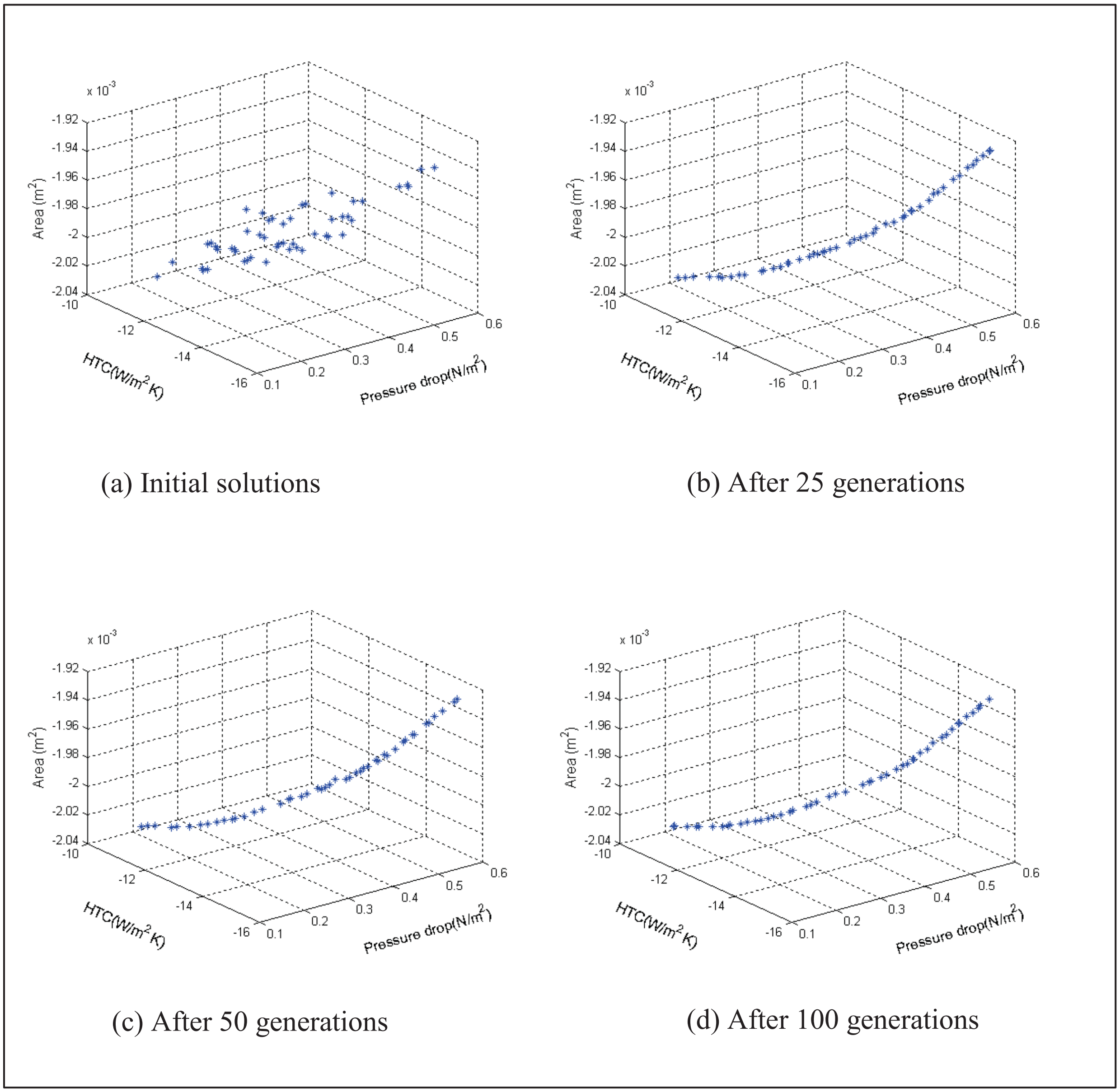
8.2 Three Objective Functions Optimization

One of the main objectives of this research investigation is introduction of third objective function that is maximization of cooling channel cavity *Area* (A). Introduction of third objective function further reduces the objective function space where Pareto-optimal solutions are found. The third objective maximization of cooling channel cavity area indirectly helps in minimizing the material consumption for blade manufacturing. This is also a very important objective considering blade material is comparatively most expensive material of all gas turbine parts.

This section presents results of cooling channel design considering three objectives- heat transfer coefficient (*h*), coolant pressure drop (Δp) and newly added objective cooling channel cavity *Area* (A). The experiments are performed with same set of evolutionary algorithm control parameters used in the single and two objective optimization discussed in Section 7.4 and Section 7.5 (i.e., Pop = 50, $Gen_{\max}$ = 100, c = 90% and m = 10%). The next three sub sections present results of optimization of h, Δp and A, for 2, 4 and 6 design variables. The objective here is to maximize the value of h, minimize the value of Δp, and maximize the value of A by varying design variable values.

8.2.1 Case 1: Two Design Variables

For Case 1, radii R_1 and R_2 (i.e., radii of Ribs 1 and 2, respectively) are considered as design variables (see Figure 7-2). The radii of these variables are varied between 1mm to 5.5mm.



(a) Initial solutions

(b) After 25 generations

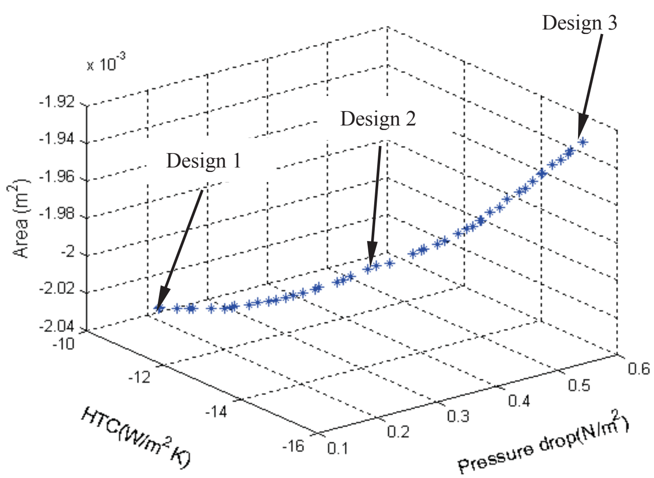
(c) After 50 generations

(d) After 100 generations

Figure 8-1: Pareto optimal front considering three objectives and two design variables

Figure 8-1 shows graphical representation of multiobjective optimization results. The y-axis represents objective function, heat transfer coefficient (h), which is to be maximized. The x-axis represents the objective function coolant pressure drop (Δp), which is to be minimized. The z-axis represents objective function the Area (A), which is to be maximized. Figure 8-1 (a) shows initial set of objective function values before being optimized. Figure 8-1 (b), (c) and (d), show solutions progressing towards Pareto optimal (efficiency) front after 25, 50 and 100 generations, respectively. For illustration purposes, in Figure 8-2 three solution values and corresponding design specifications and are used to build three designs of cooling channel as shown in Figure 8-2. Design 1 has smaller rib radii (R_1 = 1mm & R_2=1mm) resulting in a low pressure drop Δp (0.1485 N/m^2), low a heat transfer coefficient h (11.09 W/m^{2}K) and high cavity area A (0.002022m^2). Similarly, Design 3 with larger ribs (R_1 = 5.49mm & R_2=5.49mm) results in high pressure drop Δp (0.5789 N/m^2) and high heat transfer coefficient h (15.43 W/m^{2}K) and reduced cavity area A (0.00193m^2). Design 2 is selected from the mid-section of the Pareto front (R_1 = 1.025mm & R_2=4.936mm) and it results in moderate pressure drop (0.2955N/m^2), heat transfer coefficient h (14.15 W/m^{2}K) and cavity area A (0.001985m^2).

	Design 1	Design 2	Design 3
R1	0.001	0.0010254	0.00549
R2	0.001	0.0049368	0.00549
Δp	0.1485	0.3268	0.5789
h	-11.0935	-14.15	-15.43
A	-0.002022	-0.001985	-0.00193



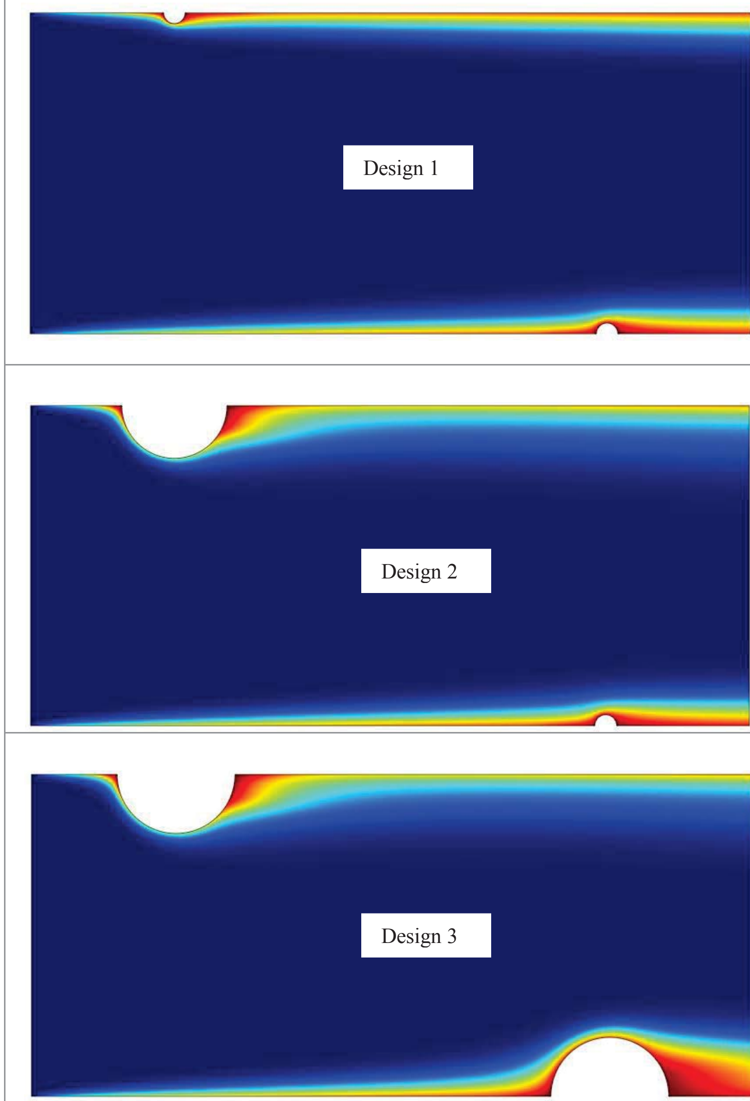
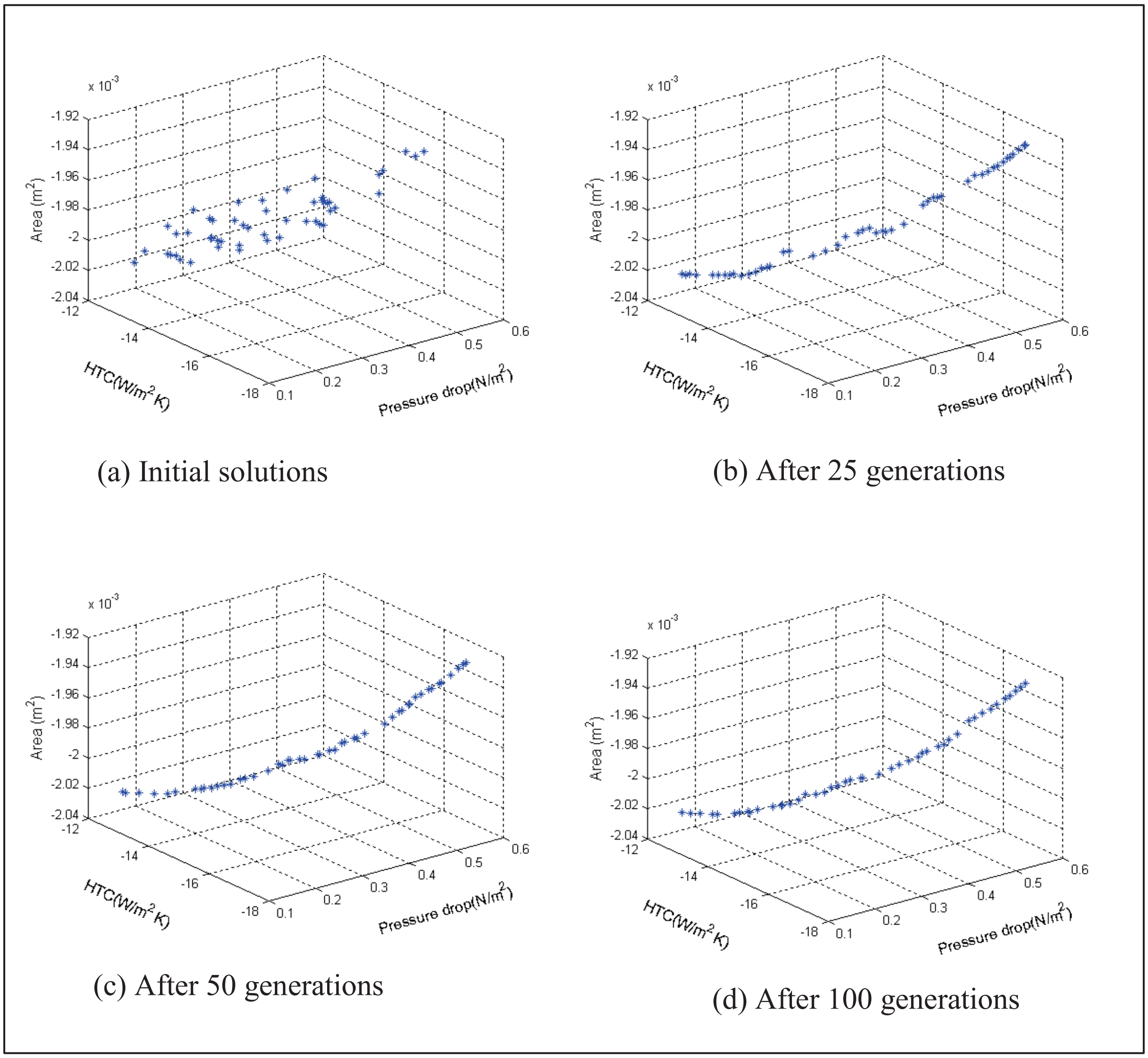


Figure 8-2: Design specifications of cooling channel for three selected optimal solutions

8.2.2 Case 2: Four Design Variables

For Case 2, radii R_1, R_2 (i.e., radii of Ribs 1 and 2, respectively) and fillets radii R_3, and R_4 are considered as design variables (Figure 7-4). The radii of ribs are varied between 1mm to 5.5mm and fillets radii are varied between 0.1mm to 0.4mm.



(a) Initial solutions (b) After 25 generations

(c) After 50 generations (d) After 100 generations

Figure 8-3: Pareto optimal front considering three objectives and four design variables

The Pareto optimal solution set each for the three objectives and the four design variables (Figure 8-3) suggest that the solutions are not converging to a smooth and uniform Pareto front in the beginning as shown in the two design variable case. Similar to two objectives and four design variables case- the solution space of the problem increases exponentially with the increase in the number of decision variables. Therefore, more search iterations (i.e., generations) with efficient search strategy (i.e., fine-tuning the search control parameters such as crossover *c* and mutation *m*) is required to explore more promising regions.

8.2.3 Case 3: Six Design Variables

For Case 3, radii R_1, R_2 (i.e., radii of Ribs 1 and 2, respectively) and fillets radii R_3, R_4, R_5, and R_6, complete set of design variables are considered (Figure 7-6). The radii of ribs are varied between 1mm to 5.5mm and fillets radii are varied between 0.1mm to 0.4mm. The Pareto front for three objectives and six design variables (Figure 8-4) further suggests that the increase in design variables decreases the progression of solution towards Pareto optimal front. As mentioned in previous sections, an increase in the number of design variables causes the solution space of the problem to increase exponentially and requires more search iterations with right control parameters values.

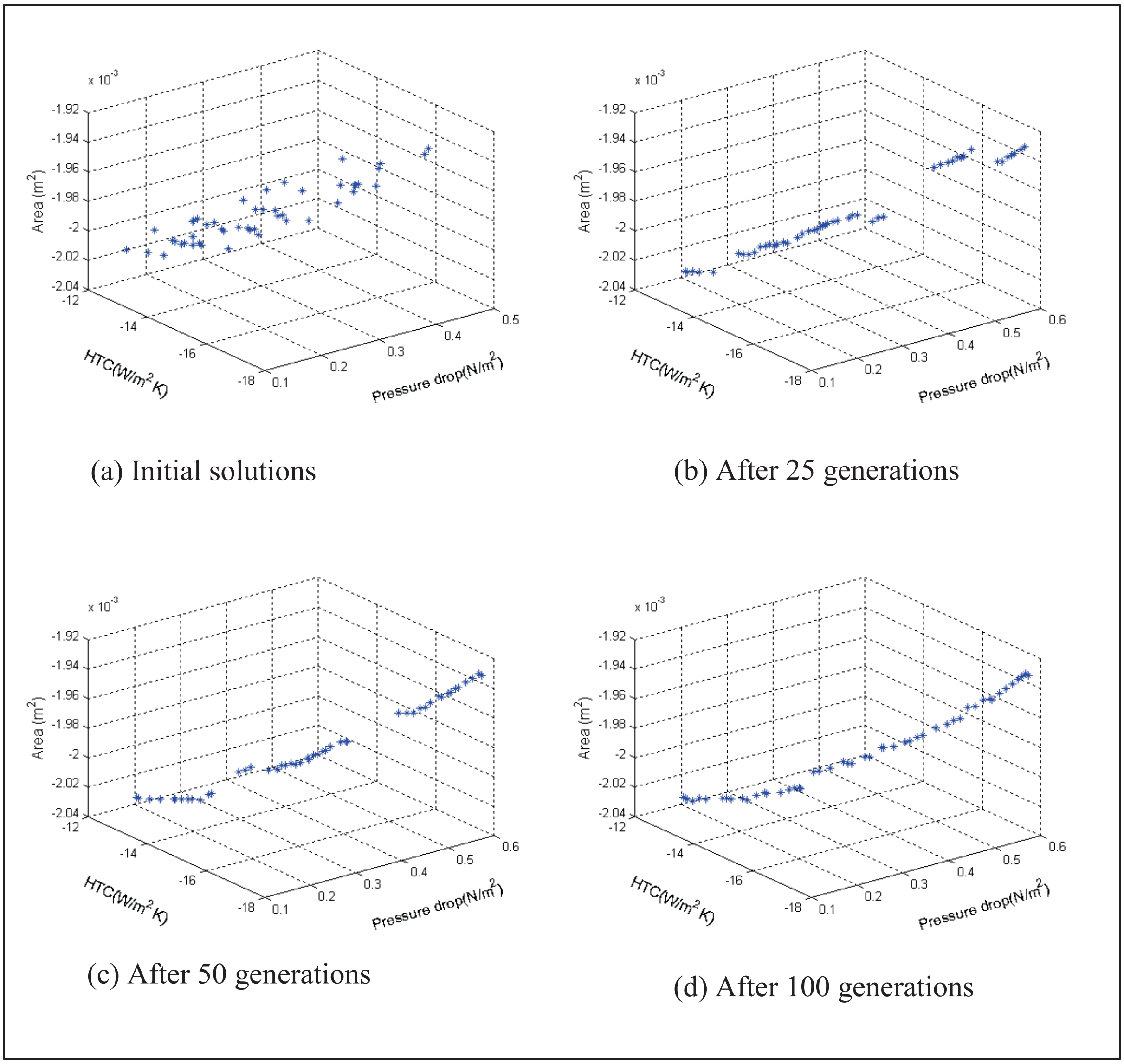
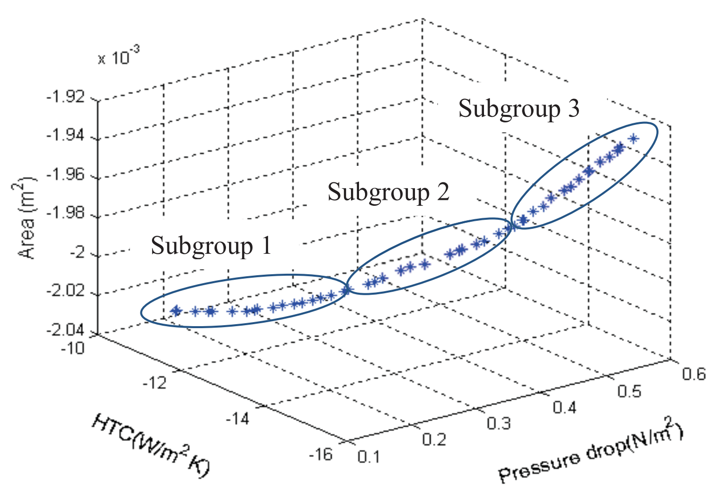


Figure 8-4: Pareto optimal front considering three objectives and six design variables

8.3 Reducing the Size of the Non-Dominated Set: Clustering

Similar to two objective Pareto optimal front clustering (Figure 7-12), three objective Pareto optimal front solutions are divided to form three subgroups (clusters) to accommodate three design types from which a designer can select the most preferred. Similar to two objective case for illustration of this technique, suppose that three types of designs are proposed (Figure

8-5). Subgroup 1 (cluster) contains the Pareto optimal solutions that satisfy objective functions minimization of *pressure drop* (Δp) and maximization of cavity *Area* (A) better than any other optimal solutions in Subgroup 2 and 3. Similarly Subgroup 3 better satisfies the maximization of heat transfer coefficient (h) objective function better than any other optimal solutions in the Subgroups 1 and 2. The Pareto optimal solutions in Subgroup 2 fall in between Subgroups 1 and 3 with moderate optimization of all three objective functions. Thus, clustering provides visual insight of solutions and aids the decision- maker in selecting solution based on objective function preferences. Although it is not within the scope of this research investigation, further research is necessary to explore the best approach to select the most preferred solution from a set Pareto optima.



Subgroup 1:
Designs in this group satisfy in minimizing objective function (Δp) and maximizing (A) at the expense of other objective function (h)

Subgroup 2:
Designs in this group moderately satisfy all three Objective functions (Δp), (h) and (A)

Subgroup 3:
Designs in this group satisfy maximizing Objective function (h) at the expense of other objective functions (Δp) and (A)

Figure 8-5: Pareto optimal front divided into three clusters of solutions

8.4 Summary

The Evolutionary algorithm NSGA-II and CFD tool COMSOL is successfully applied to an automated optimization of a gas turbine blade cooling channel configuration. The optimization is performed in an automated fashion to an optimal solution during maximization of heat transfer coefficient (h) in single objective optimization. Next an experimental results of nondominated Pareto optimal front in maximization of heat transfer coefficient (h) and minimization of pressure drop (Δp) for two objective optimization. Finally results of nondominated Pareto optimal front for maximization of heat (h), minimization of (Δp) and maximization cooling channel cavity Area (A).

The experimental results showed more insight in understanding of the physical problem by showing the correlation between design variables and objective functions. This automated optimization framework can be considered a supporting tool in the design process, complementing physical understanding as well as experimental design and computational design process.

CHAPTER 9:
SUMMARY AND FUTURE RESEARCH DIRECTIONS

9.1 Research Summary

Multiobjective optimization of engineering design problems in an automated setup requires blending of domain knowledge with expertise in optimization techniques. Evaluation and identification of the problem specific requirements is always the fore runner in setting up an automated optimization process. Then, an optimization algorithm (Optimizer) is chosen with respect to the problem requirements. Motivated by the need for reliable and highly efficient power plant gas turbines to meet the exponentially growing energy demand, this research investigation has successfully created and demonstrated a framework to optimize design specification of a complex gas turbine blade cooling channel by satisfying three conflicting objectives simultaneously. The gas turbine blade cooling design optimization known to increase the life of gas turbine and also increase efficiency and power output. The broader impact of the proposed research to revolutionize the mechanical component design process lies in the understanding and advancement of efficient integration of evolutionary algorithms and numerical simulation.

It has been shown that evolutionary algorithms are powerful, intelligent optimization algorithms that are able to balance exploration and exploitation of the solution search space. The drawbacks of traditional approaches, which typically try to scalarize the multiple objectives into a single composite objective, have motivated researchers and practitioners to seek alternative techniques to find a set of Pareto optimal solutions rather than just a single optimal solution.

Likewise, numerical simulation in mechanical component design plays a significant role in complementing analytical and experimental design process. They are excellent in simulating physical environment and subjecting test components to various types of loads they undergo in reality. This computational simulation environment enables designer to test and observe the behavior of the designs before they are subjected to more expensive experimental methods. The application of numerical simulation to mechanical component design was hindered till recent due to computational capabilities. The advent of high speed computers and affordability of such computers practically made numerical simulation a must in most of the design process today.

Numerical simulation allows flexibility in exploring different designs of mechanical component while evolutionary algorithms have ability to evolve and optimize them. Based on the proposed optimization framework, an optimal blade cooling channel configuration design could be successfully obtained even with the absence of auxiliary knowledge or analytical information in the problem formulation. Similarly, an initial population (solution) made up of all bad designs did not impede the ability of the optimization algorithm in finding better feasible Pareto optimal solutions. Thus it can be said that evolutionary optimization techniques are robust even in the complex search space of cooling channel design problem.

The research investigation undertaken is a modest attempt to bridge the gap between multiobjective optimization evolutionary algorithms (MOEAs) and numerical simulation to automate evolution of mechanical design process. In CHAPTER 2, we review the literature of optimization techniques both direct and non-direct methods used in mechanical component design. We also reviewed more relevant literature related to blade cooling channel designs where researchers have investigated multiobjective optimization with two objective functions. They solve these problems both constructing one composite objective function and giving weightage to objective functions incorporated to composite function or by solving objective functions separately and mapping solutions to find set of optimal solutions. It is shown that there has been no other work that considered multiple objectives simultaneously for optimization. This research investigation considers three conflicting objective functions for optimizations by varying range up to six design variables.

CHAPTER 3 briefly describes physics of heat transfer and fluid flow phenomenon along with governing equations to help understand the cooling channel problem. To evaluate designs, these governing equations need to be solved using numerical simulation code to simulate the heat transfer and fluid flow behavior inside cooling channel. CHAPTER 4 introduces second generation multiobjective optimization algorithm called Non-dominated Sorting Genetic Algorithm (NSGA-II) and its working principle.

CHAPTER 5 presents the framework of the proposed multiobjective optimization system, which is comprised of an Optimizer and Simulator. The Optimizer uses NSGA-II to perturb the design variables to evolve the optimal solution from generation to generation. The Simulator a commercially-available CFD tool (COMSOL) evaluates the objective functions for corresponding perturbed design variables it receives from Optimizer. Both Optimizer and Simulator are integrated and automated to perform the optimization of multiple objectives with only a few inputs in the beginning. CHAPTER 6 introduces the optimization of real-world objective functions, the process of selection of design variables and presents the graphical results of computational simulation of blade cooling channel. Also presented is a pilot study that is for the selection of the experimental search of control parameters for the Optimizer component. A population size (*Pop*) of 50, number of generations (Gen_{max}) of 100, crossover (*c*) and mutation (*m*) probability of 90% and 10% respectively are found to be appropriate parameters for this research investigation.

In CHAPTER 7, a brief literature on conventional and non-conventional cooling channel design optimization specific to this research investigation is presented. Existing literature for the conventional method using experimental and numerical techniques are presented, whereas literature for non-conventional methods which use response surface methodology and other optimization algorithms are presented. Also presented in this chapter are the results of one and two objective optimization problem. CHAPTER 8 is dedicated to the optimization of three objective functions. The three objective functions identified to optimize in this investigation are heat transfer coefficient (*h*), cooling channel pressure drop (Δp) and cooling channel cavity area (*A*).

The multiobjective optimization process performed for one, two and three objectives by varying two, four and six design variables within prescribed range of values. The population size of 50 and 100 generations performed 5000 design evaluations in an average of 5 to 6 days before the Pareto optimal frontier comprising 50 optimal solutions are obtained. These optimal fronts are further clustered to form subgroup of optimal solutions which dominate in one objective over the other. These clustering techniques increase designer's decision making capability by providing flexibility in choosing designs with visual representation of trade-off information between the conflicting multiple objectives. With a clearer understanding of the system, the designer can have a better awareness of the priorities among the objectives before making well-informed decisions.

From this research investigation, the MOEA and Numerical Simulation integration proved to be more reliable and efficient than the Response Surface Method (RSM). It is also easier to use and more generalized in this investigation for the gas turbine blade cooling channel design application. Since the cooling channel design is multiobjective in nature, solving it as a multiobjective optimization problem proved to be the better approach.

9.2 Future Research Directions

We are confident that the research investigation presented and the conclusion drawn has laid sufficient foundation for the following possible extension of this investigation for future research. In cooling channel design optimization, the main areas for improvements are enhancing the speed and robustness of the process. Application of the proposed framework to other design optimization areas such as Mechanical systems, Civil engineering, Nanotechnology may pose excellent opportunity for optimization. Some of the potential future works are as follows:

9.2.1 Reduce the Computational Effort

The main drawback of using evolutionary techniques with numerical simulation to optimize the design of mechanical component is that it can be computationally expensive as it requires many designs/function evaluations. However, the ever improving computer technology and the option of parallel processing can lead to faster performance. The parallel processing techniques can be applied to distribute the computational workload among different processors or computers. Due to the nature of genetic algorithm that deals with a population of solution in parallel, this technique is also very suitable and straightforward. With proper allocation of job and communication of results between processing cores, the reduction of total optimization time can be multi-fold.

9.2.2 Expand the Design Optimization Applications

The proposed optimization framework was tested on cooling channel design optimization; the next immediate step is to apply the frame work for further enhancement of cooling channel with following potential future works as follows:

1. Introduce other design variables which influence the objective functions values. Example: The Pitch (distance between ribs), the angle of ribs (orientation of ribs):
2. Enhance the framework with introduction of three dimensional (3D) models.
3. Vary simulation parameters, such as velocity of flow (Reynolds number), pressure and temperature.
4. The other interesting problem to test in future study is introduction of mix of turbulator shapes with different sizes as shown in Figure 9-1.
5. Finally introducing this framework to other fields of engineering design with multiple conflicting objectives is an attractive opportunity.

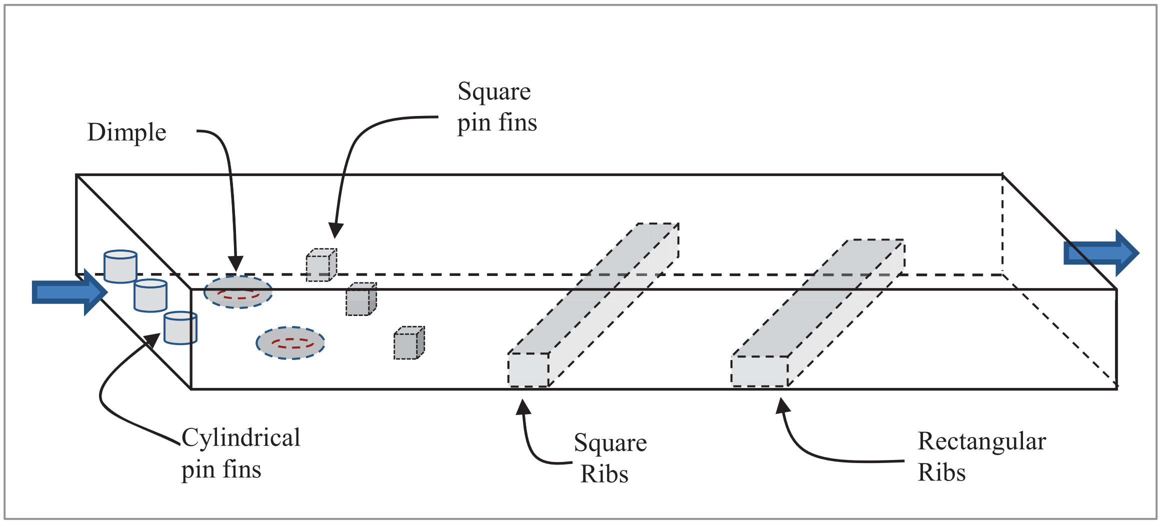
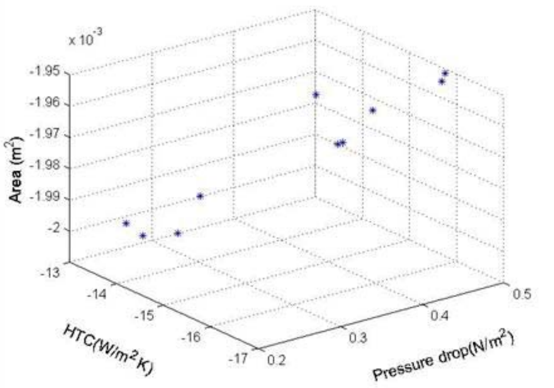


Figure 9-1: Cooling channel turbulators with different shapes

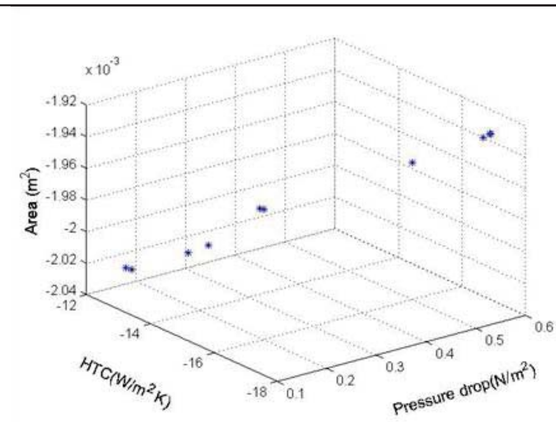
APPENDIX A: PILOT STUDY RESULTS

Pilot Study 1

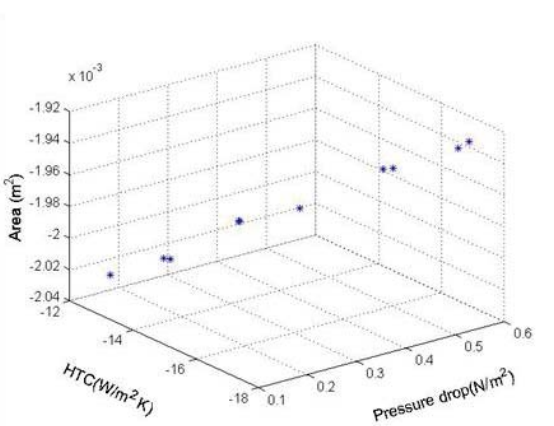
Population size (*Pop*) = 10	Generations (Gen_{max}) =100
Crossover (*c*) = 0.80 (80%)	Mutation Probability (*m*) = 0.05 (5%)



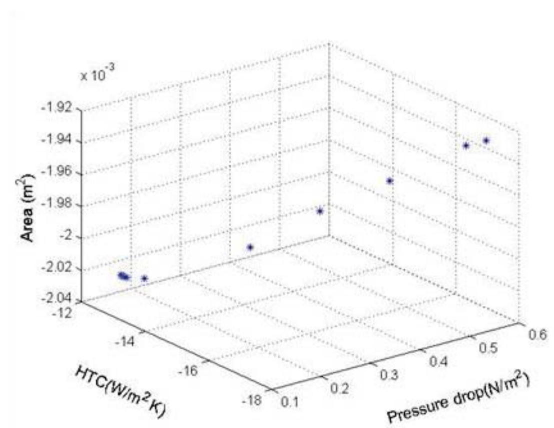
(a) Initial solutions



(b) After 25 generations



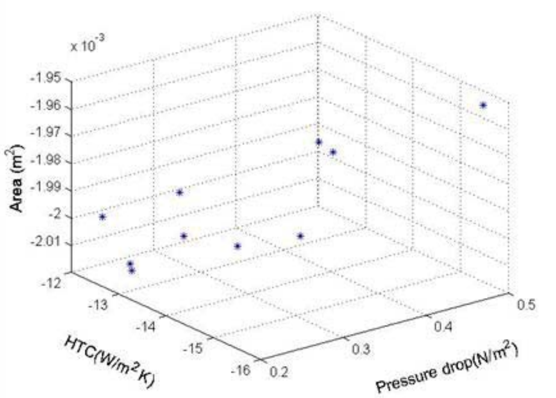
(c) After 50 generations



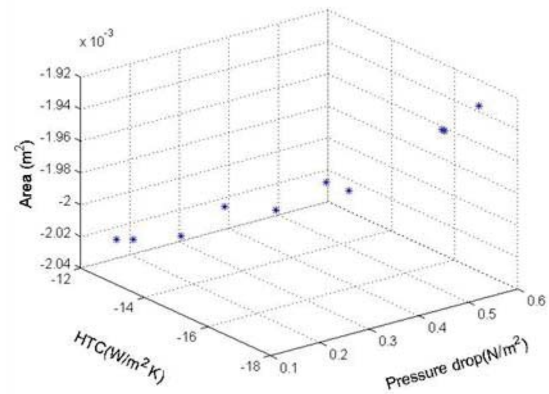
(d) After 100 generations

Pilot Study 2

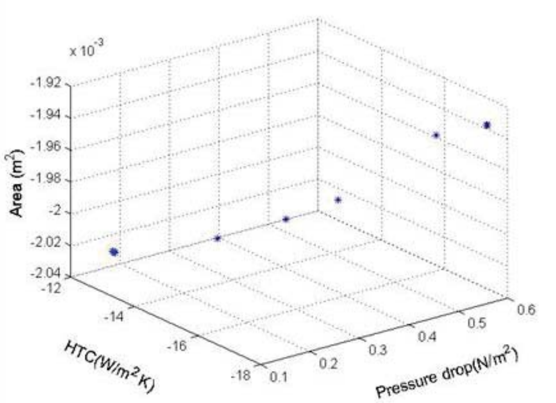
Population size (*Pop*) = 10	Generations (Gen_{max}) =100
Crossover (*c*) = 0.80 (80%)	Mutation Probability (*m*) = 0.10 (10%)



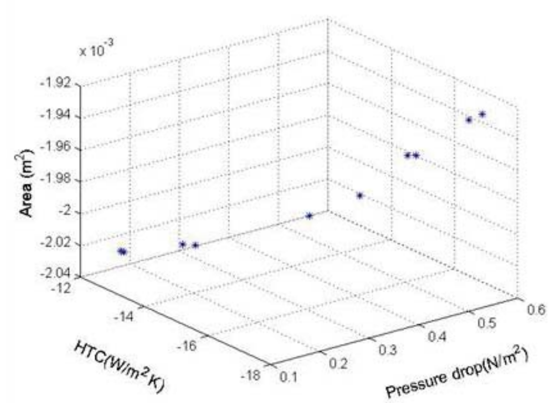
(a) Initial solutions



(b) After 25 generations



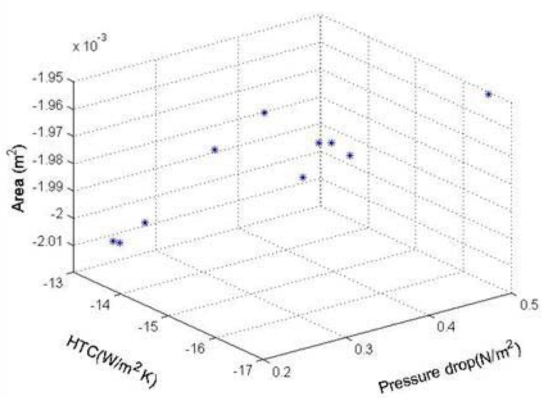
(c) After 50 generations



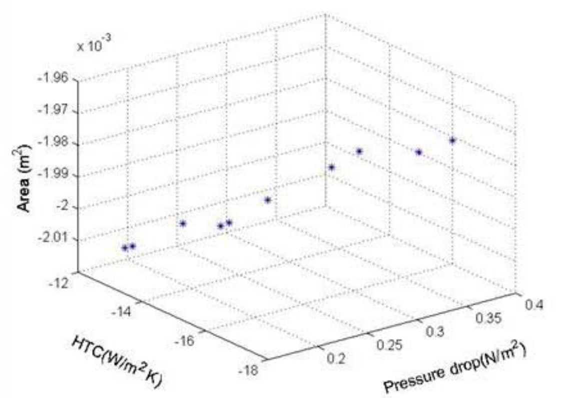
(d) After 100 generations

Pilot Study 3

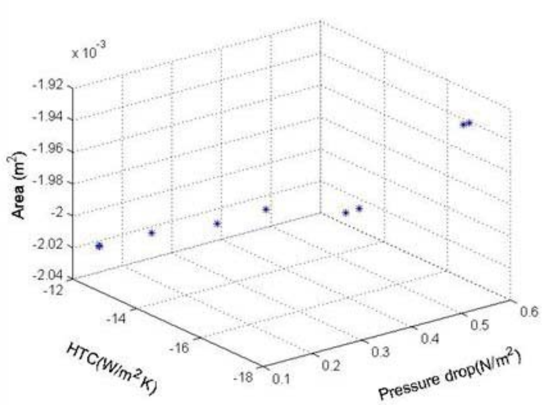
Population size (*Pop*) = 10	Generations (Gen_{max}) =100
Crossover (*c*) = 0.90 (90%)	Mutation Probability (*m*) = 0.05 (5%)



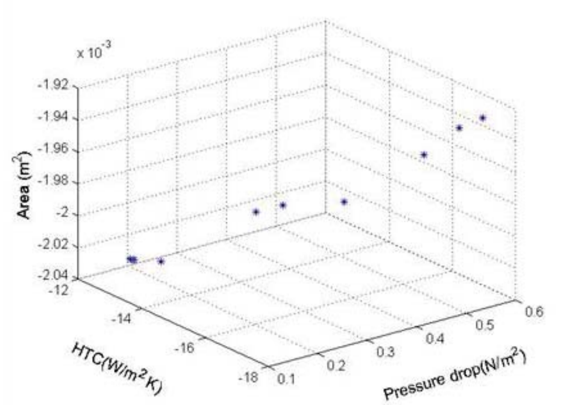
(a) Initial solutions



(b) After 25 generations



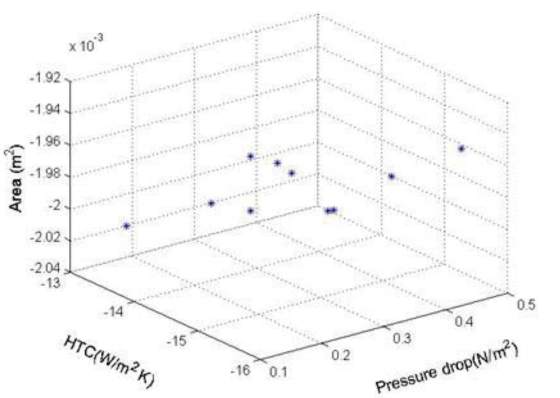
(c) After 50 generations



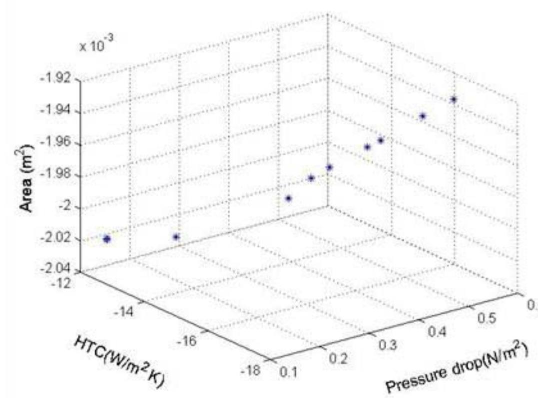
(d) After 100 generations

Pilot Study 4

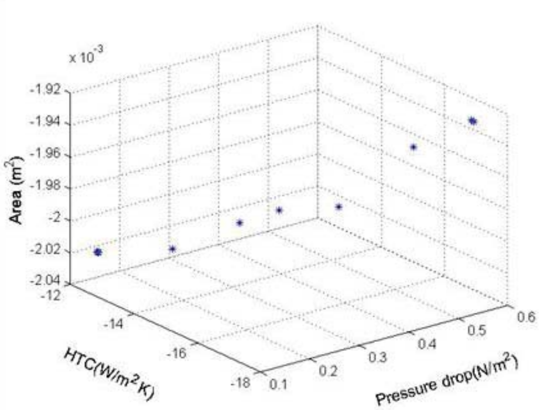
Population size (*Pop*) = 10	Generations (Gen_{max}) =100
Crossover (*c*) = 0.90 (90%)	Mutation Probability (*m*) = 0.10 (10%)



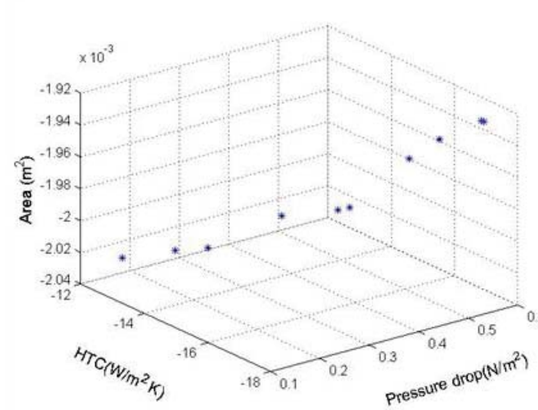
(a) Initial solutions



(b) After 25 generations



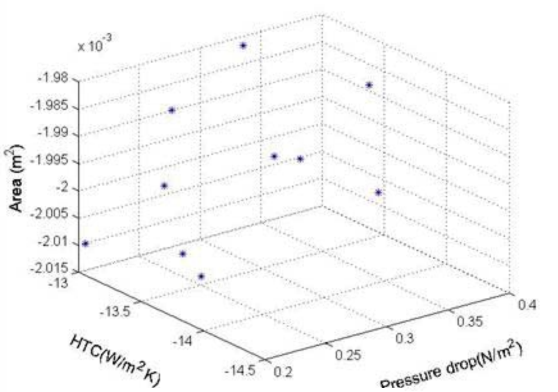
(c) After 50 generations



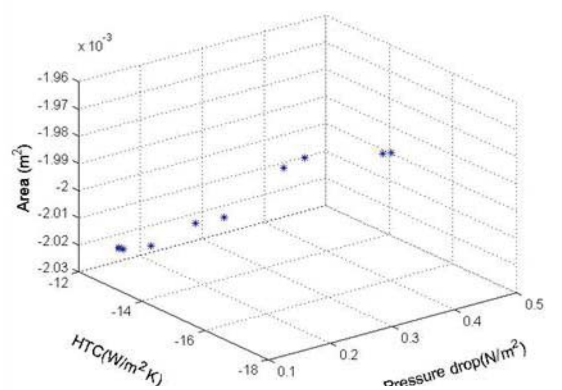
(d) After 100 generations

Pilot Study 5

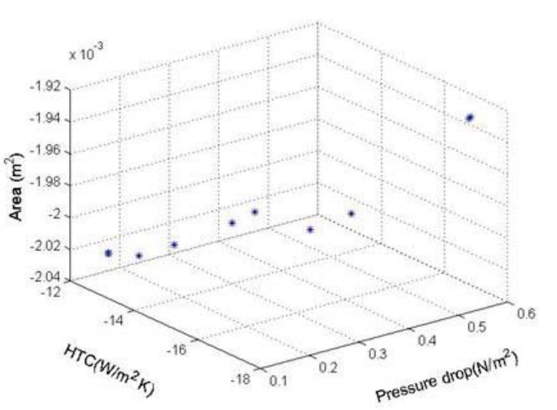
Population size (*Pop*) = 10	Generations (Gen_{max}) =100
Crossover (*c*) = 0.95 (95%)	Mutation Probability (*m*) = 0.05 (5%)



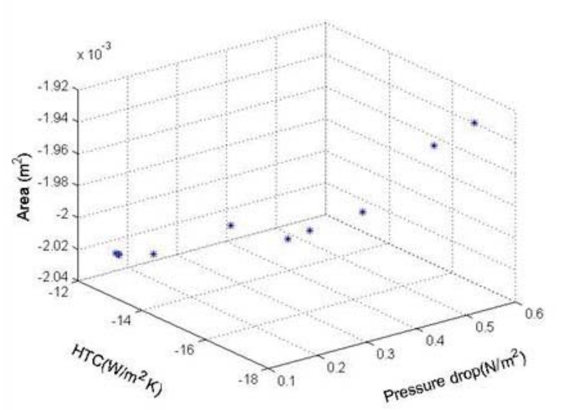
(a) Initial solutions



(b) After 25 generations



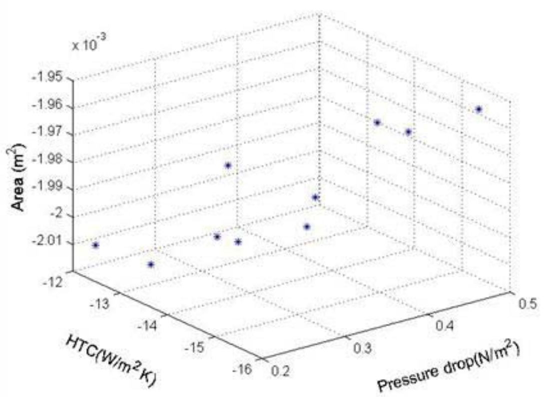
(c) After 50 generations



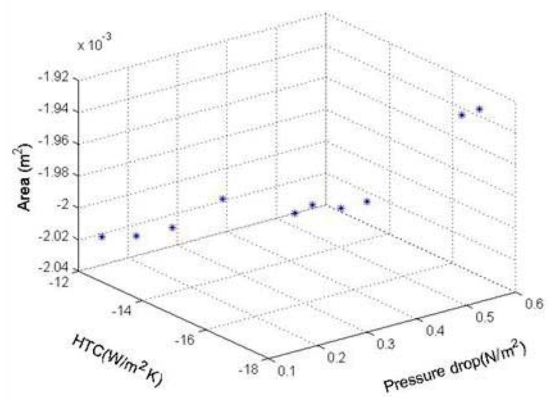
(d) After 100 generations

Pilot Study 6

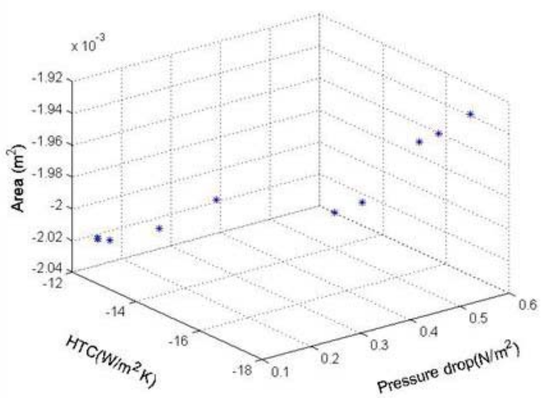
Population size (*Pop*) = 10	Generations (Gen_{max}) =100
Crossover (*c*) = 0.95 (95%)	Mutation Probability (*m*) = 0.10 (10%)



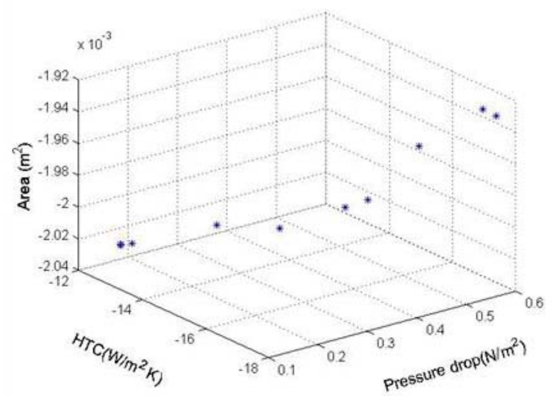
(a) Initial solutions



(b) After 25 generations



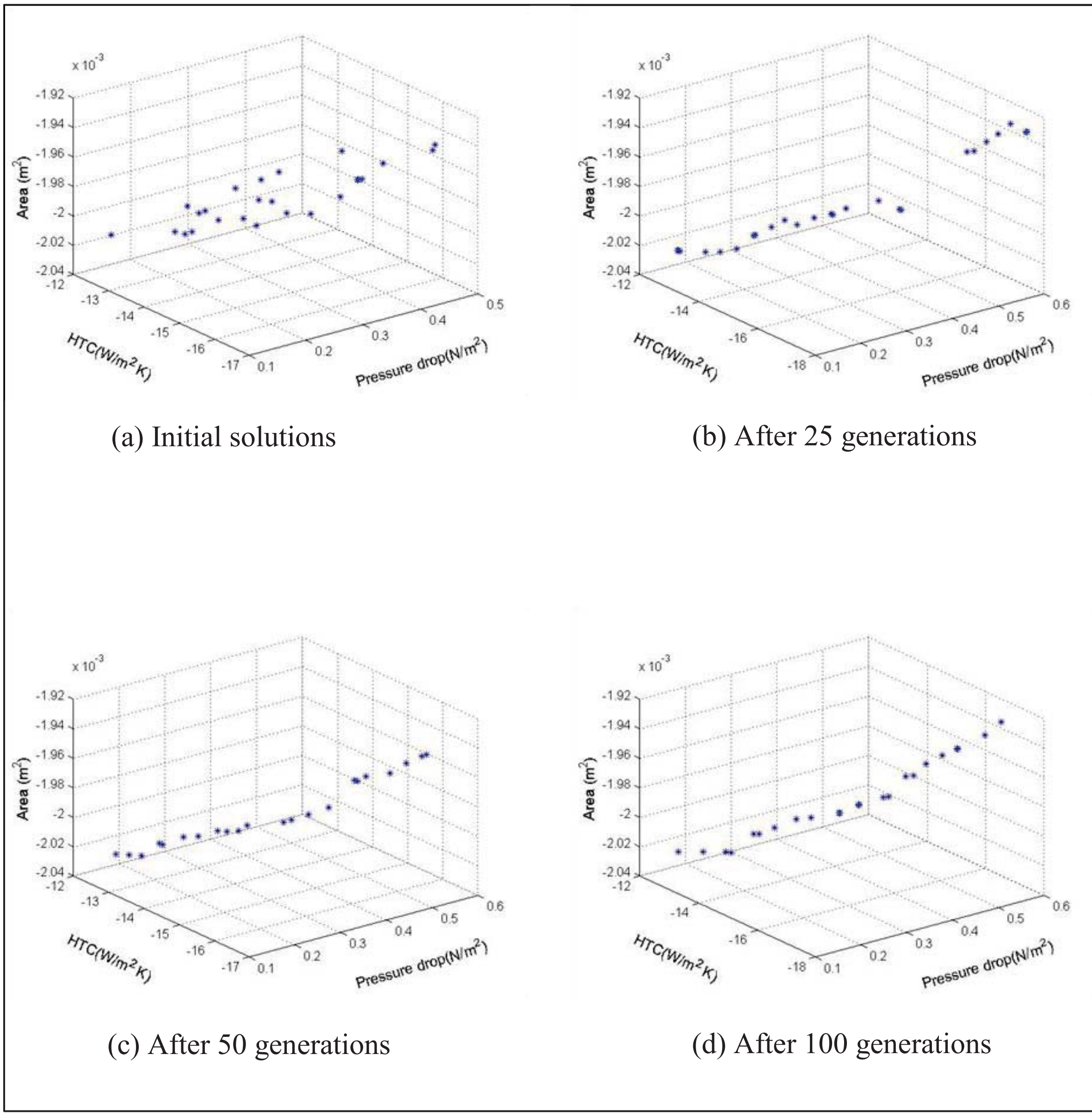
(c) After 50 generations



(d) After 100 generations

Pilot Study 7

Population size (*Pop*) = 25	Generations (Gen_{max}) =100
Crossover (*c*) = 0.80 (80%)	Mutation Probability (*m*) = 0.05 (5%)



(a) Initial solutions

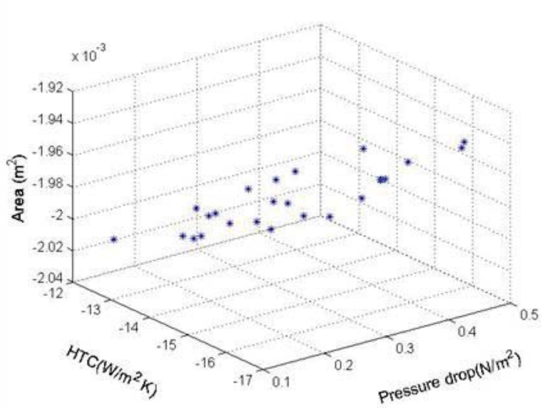
(b) After 25 generations

(c) After 50 generations

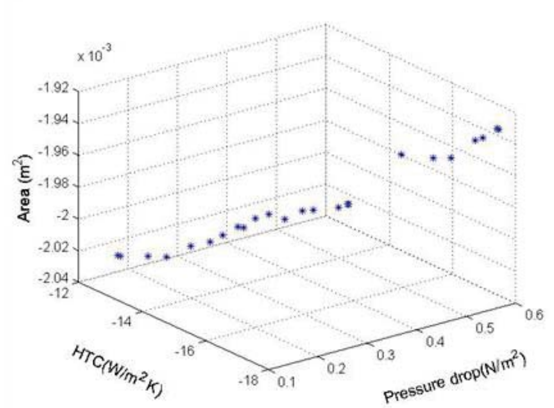
(d) After 100 generations

Pilot Study 8

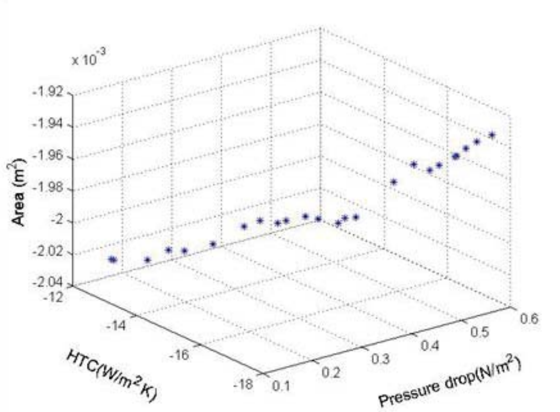
Population size (*Pop*) = 25	Generations (Gen_{max}) =100
Crossover (*c*) = 0.80 (80%)	Mutation Probability (*m*) = 0.10 (10%)



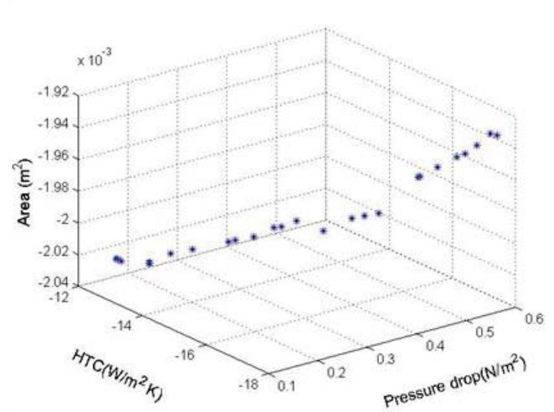
(a) Initial solutions



(b) After 25 generations



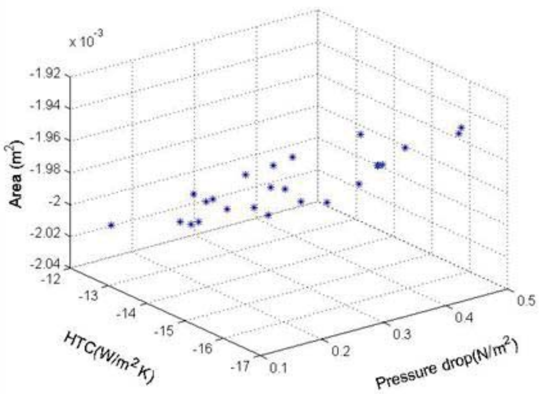
(c) After 50 generations



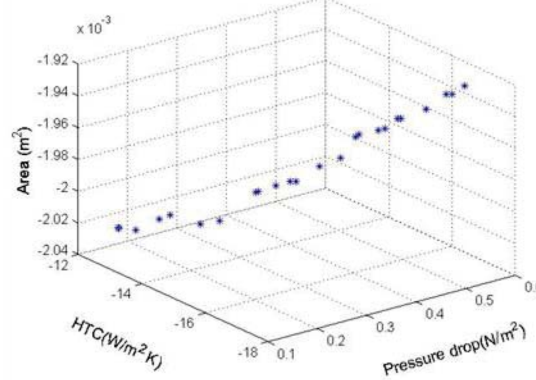
(d) After 100 generations

Pilot Study 9

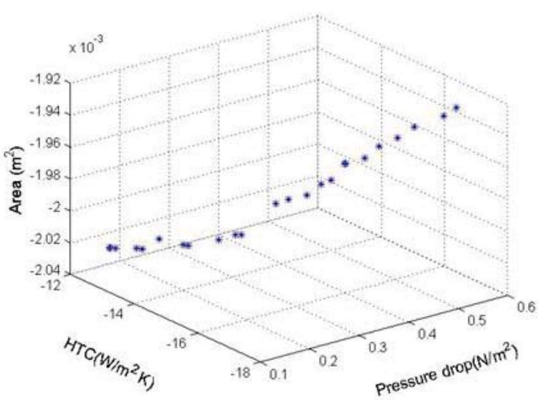
Population size (*Pop*) = 10	Generations (Gen_{max}) =100
Crossover (c) = 0.90 (90%)	Mutation Probability (m) = 0.05 (5%)



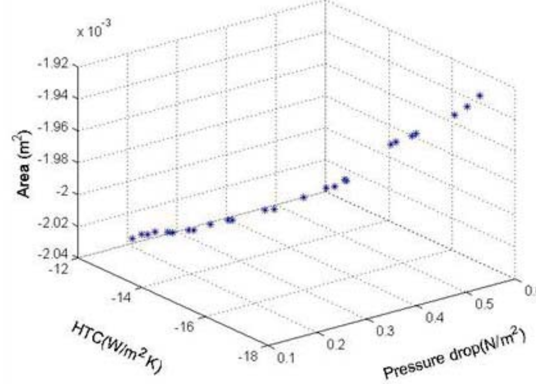
(a) Initial solutions



(b) After 25 generations



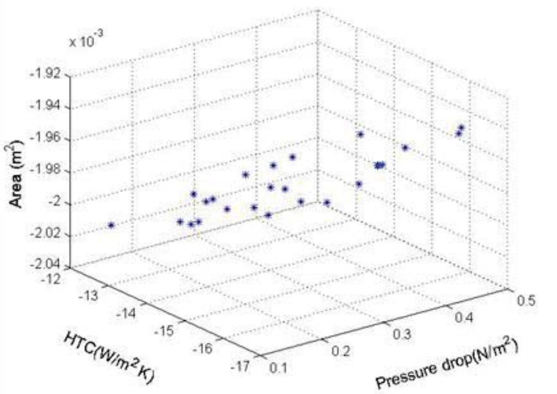
(c) After 50 generations



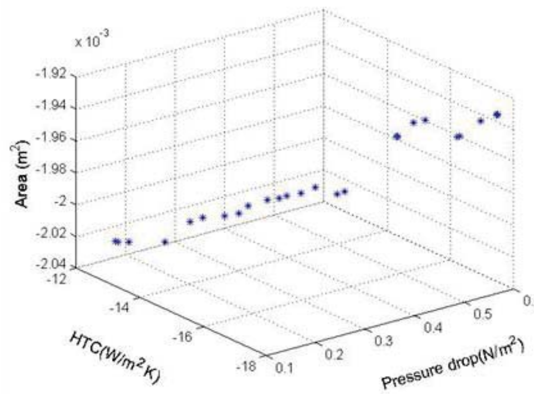
(d) After 100 generations

Pilot Study 10

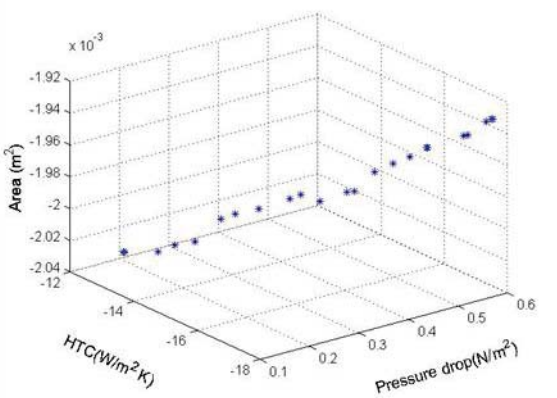
Population size (*Pop*) = 25	Generations (Gen_{max}) =100
Crossover (*c*) = 0.90 (90%)	Mutation Probability (*m*) = 0.10 (10%)



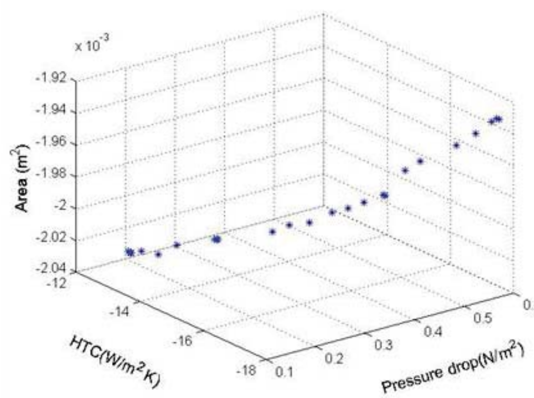
(a) Initial solutions



(b) After 25 generations



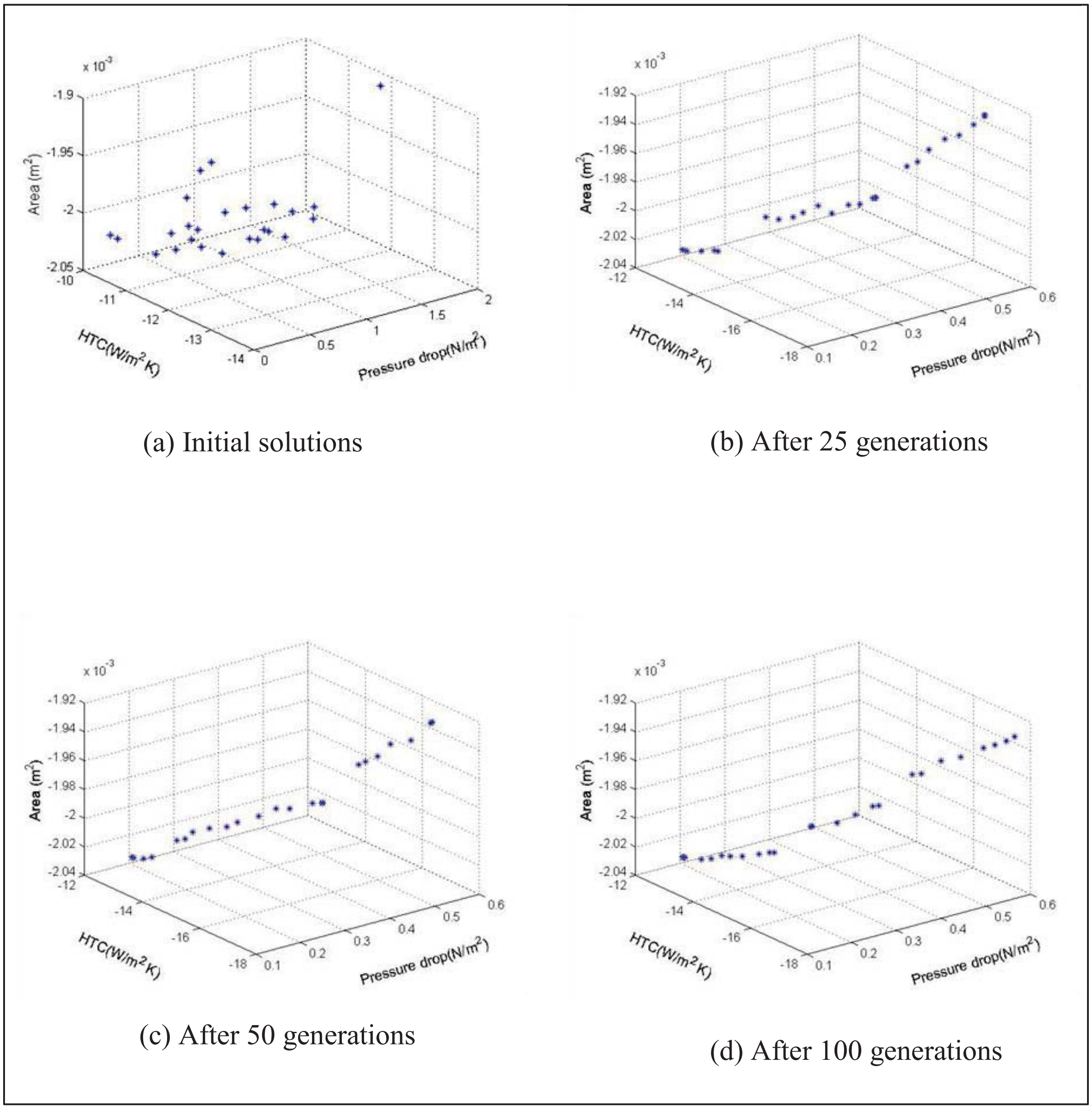
(c) After 50 generations



(d) After 100 generations

Pilot Study 11

Population size (*Pop*) = 25	Generations ($Gen_{\max}$) =100
Crossover (*c*) = 0.95 (95%)	Mutation Probability (*m*) = 0.05 (5%)



(a) Initial solutions

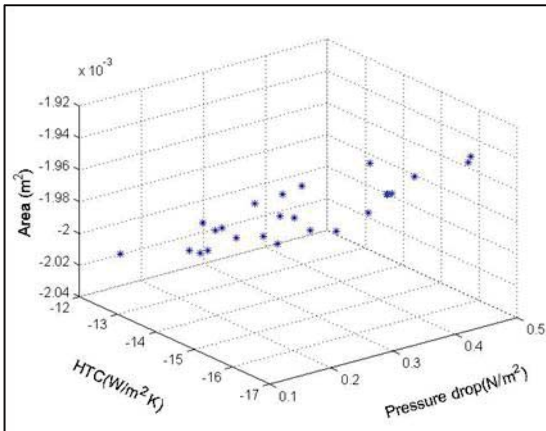
(b) After 25 generations

(c) After 50 generations

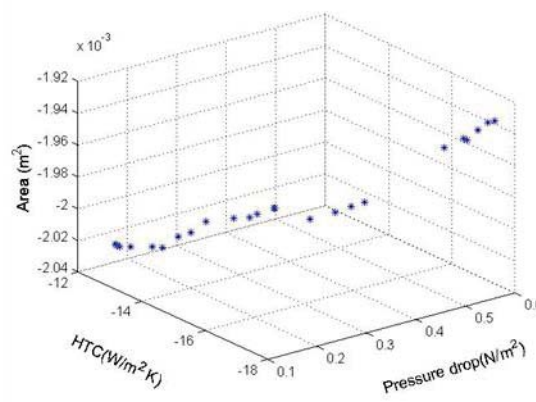
(d) After 100 generations

Pilot Study 12

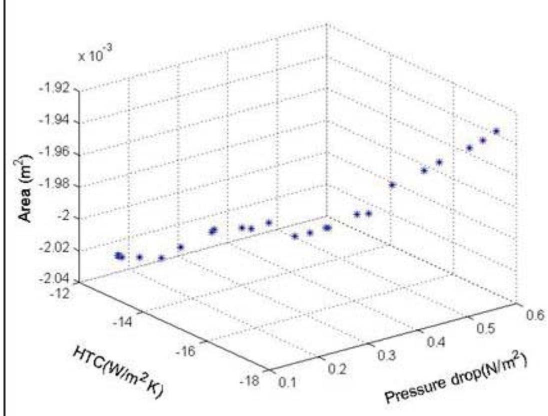
Population size (*Pop*) = 25	Generations (Gen_{max}) =100
Crossover (*c*) = 0.95 (95%)	Mutation Probability (*m*) = 0.10 (10%)



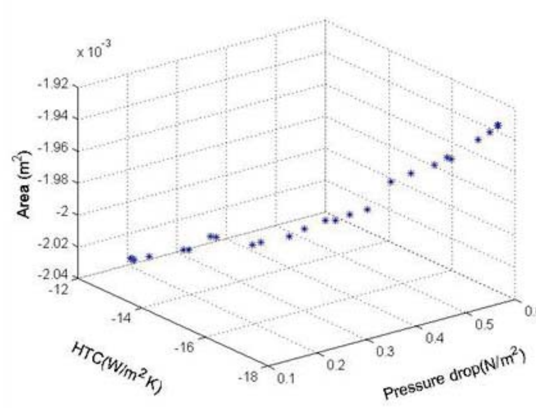
(a) Initial solutions



(b) After 25 generations



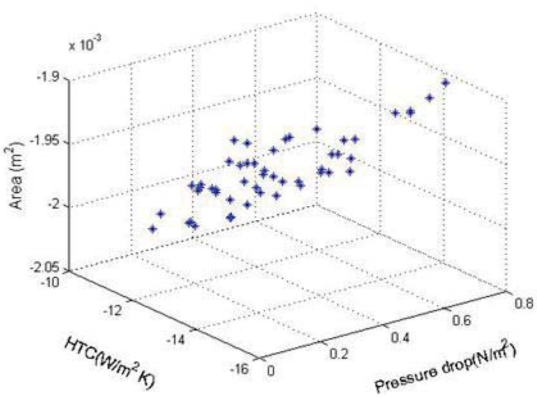
(c) After 50 generations



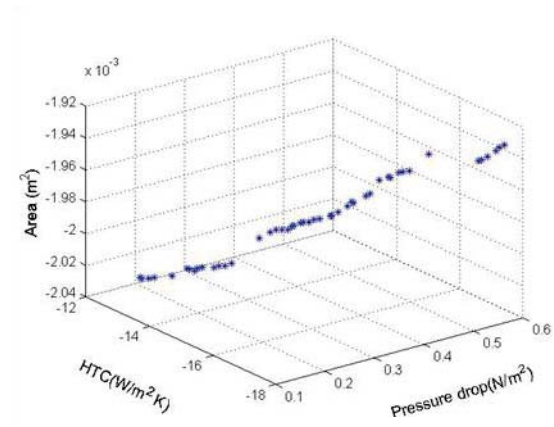
(d) After 100 generations

Pilot Study 13

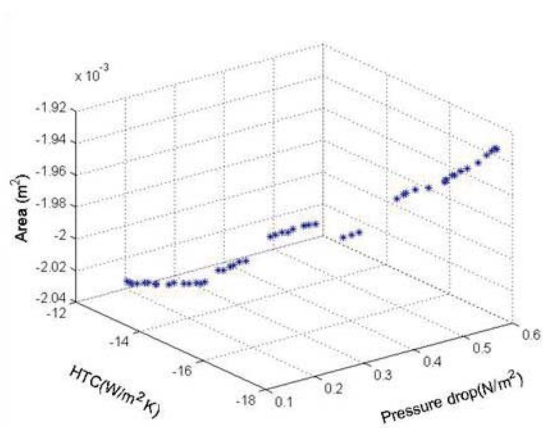
Population size (*Pop*) = 50	Generations (Gen_{max}) =100
Crossover (*c*) = 0.80 (80%)	Mutation Probability (*m*) = 0.05 (5%)



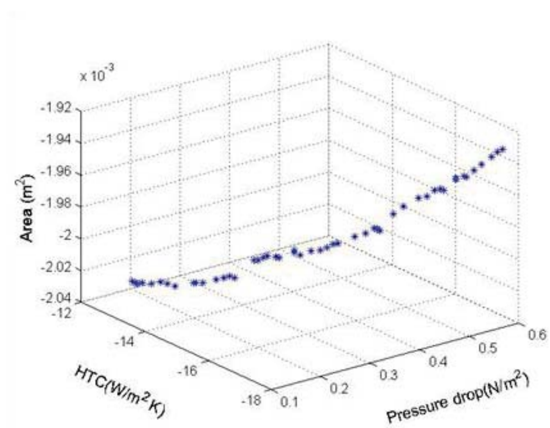
(a) Initial solutions



(b) After 25 generations



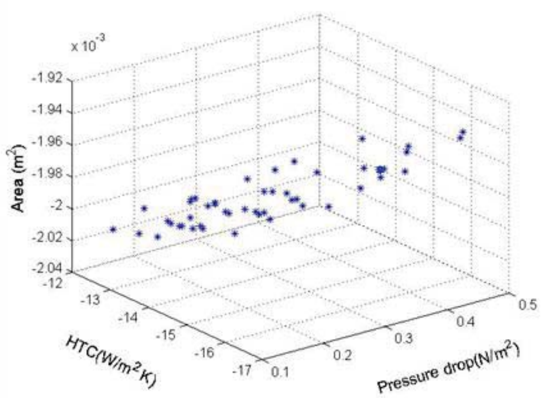
(c) After 50 generations



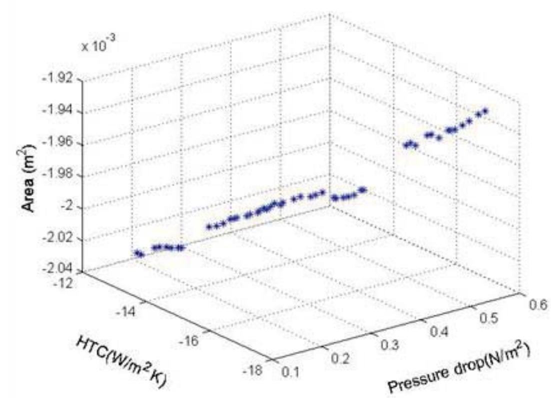
(d) After 100 generations

Pilot Study 14

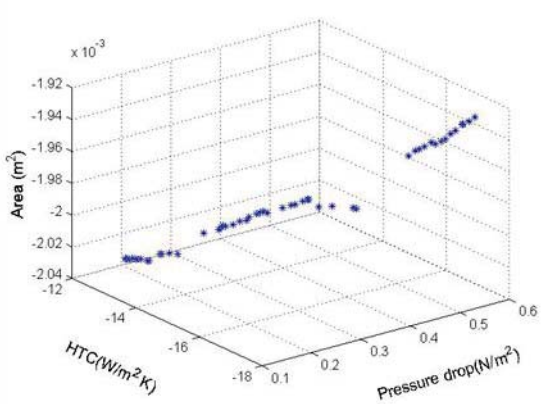
Population size (*Pop*) = 50	Generations (Gen_{max}) =100
Crossover (*c*) = 0.80 (80%)	Mutation Probability (*m*) = 0.10 (10%)



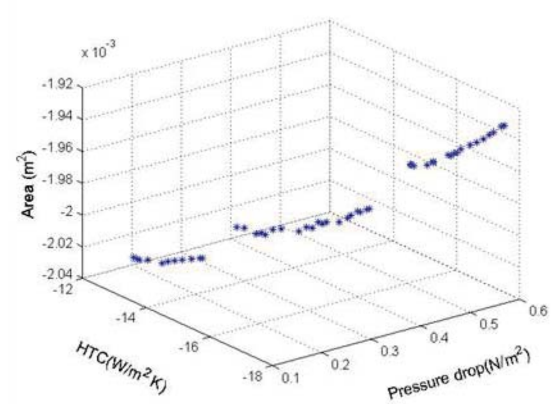
(a) Initial solutions



(b) After 25 generations



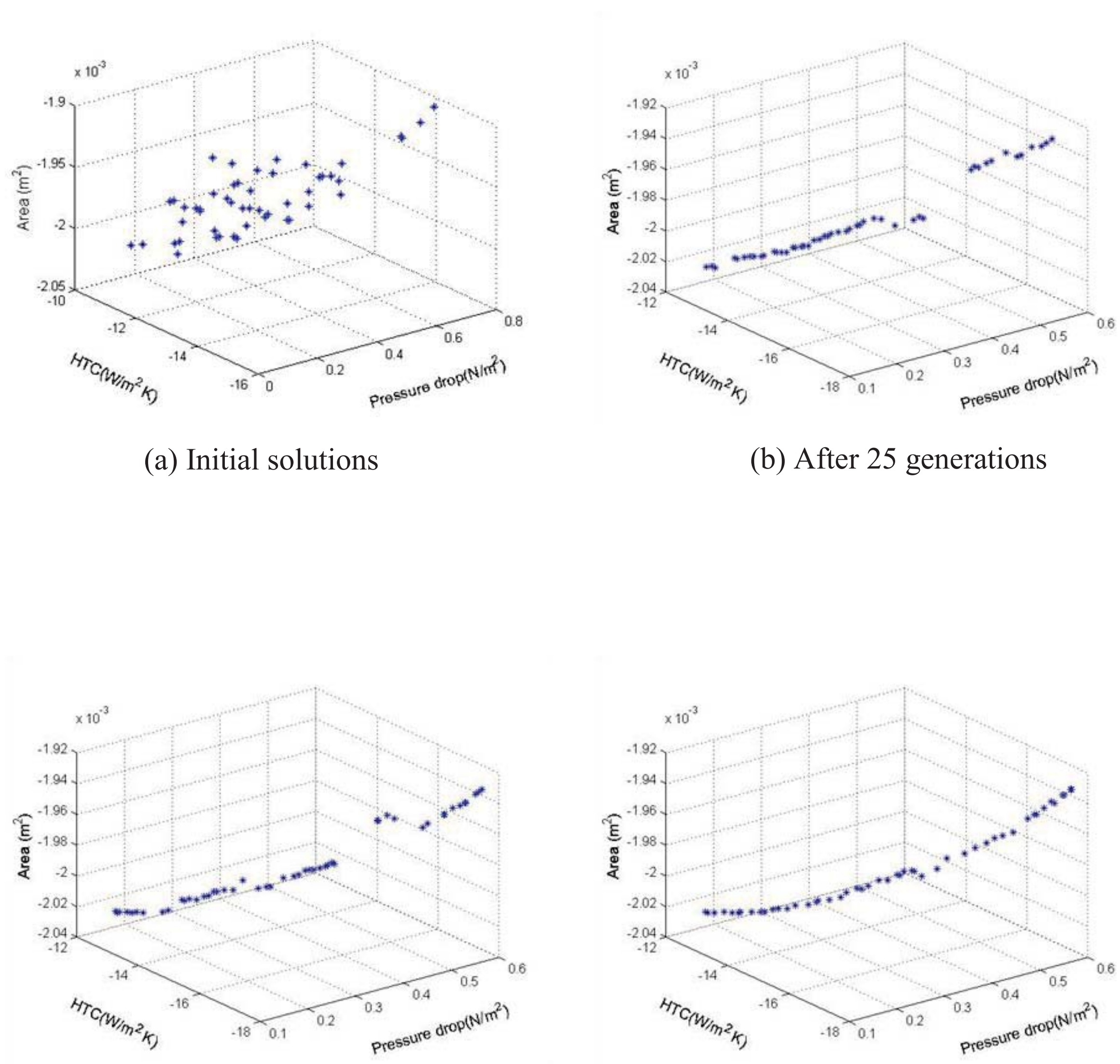
(c) After 50 generations



(d) After 100 generations

Pilot Study 15

Population size (*Pop*) = 50	Generations (Gen_{max}) =100
Crossover (*c*) = 0.90 (90%)	Mutation Probability (*m*) = 0.05 (5%)



(a) Initial solutions

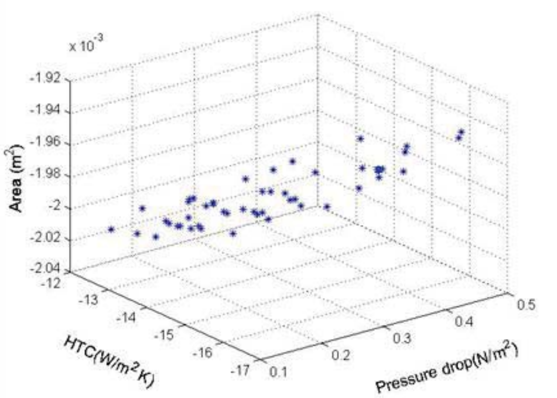
(b) After 25 generations

(c) After 50 generations

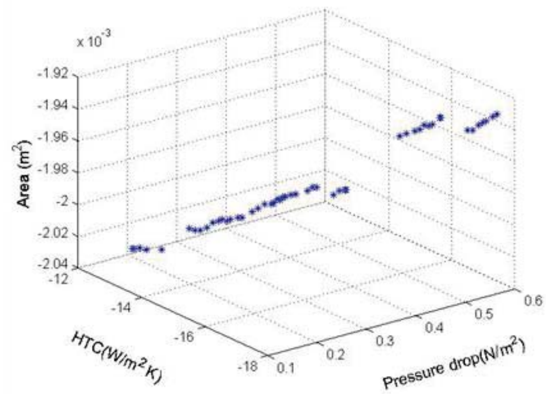
(d) After 100 generations

Pilot Study 16

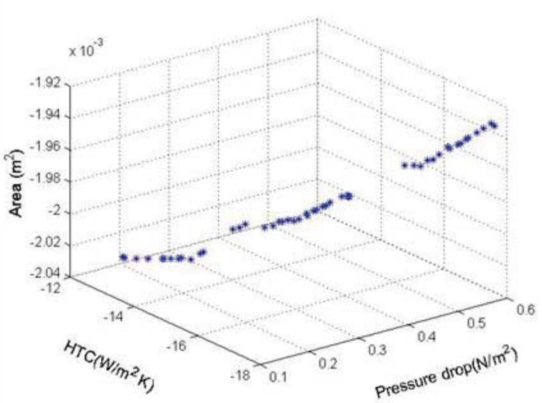
Population size (*Pop*) = 50	Generations (Gen_{max}) =100
Crossover (*c*) = 0.90 (90%)	Mutation Probability (*m*) = 0.10 (10%)



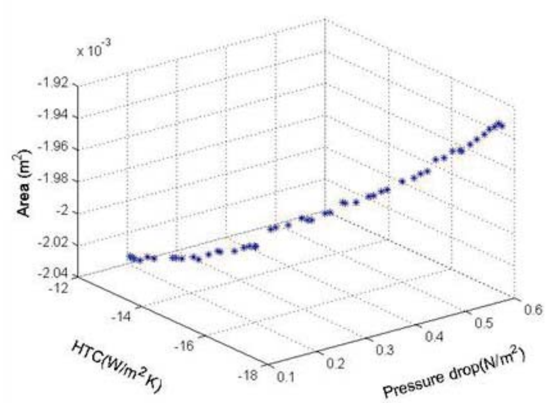
(a) Initial solutions



(b) After 25 generations



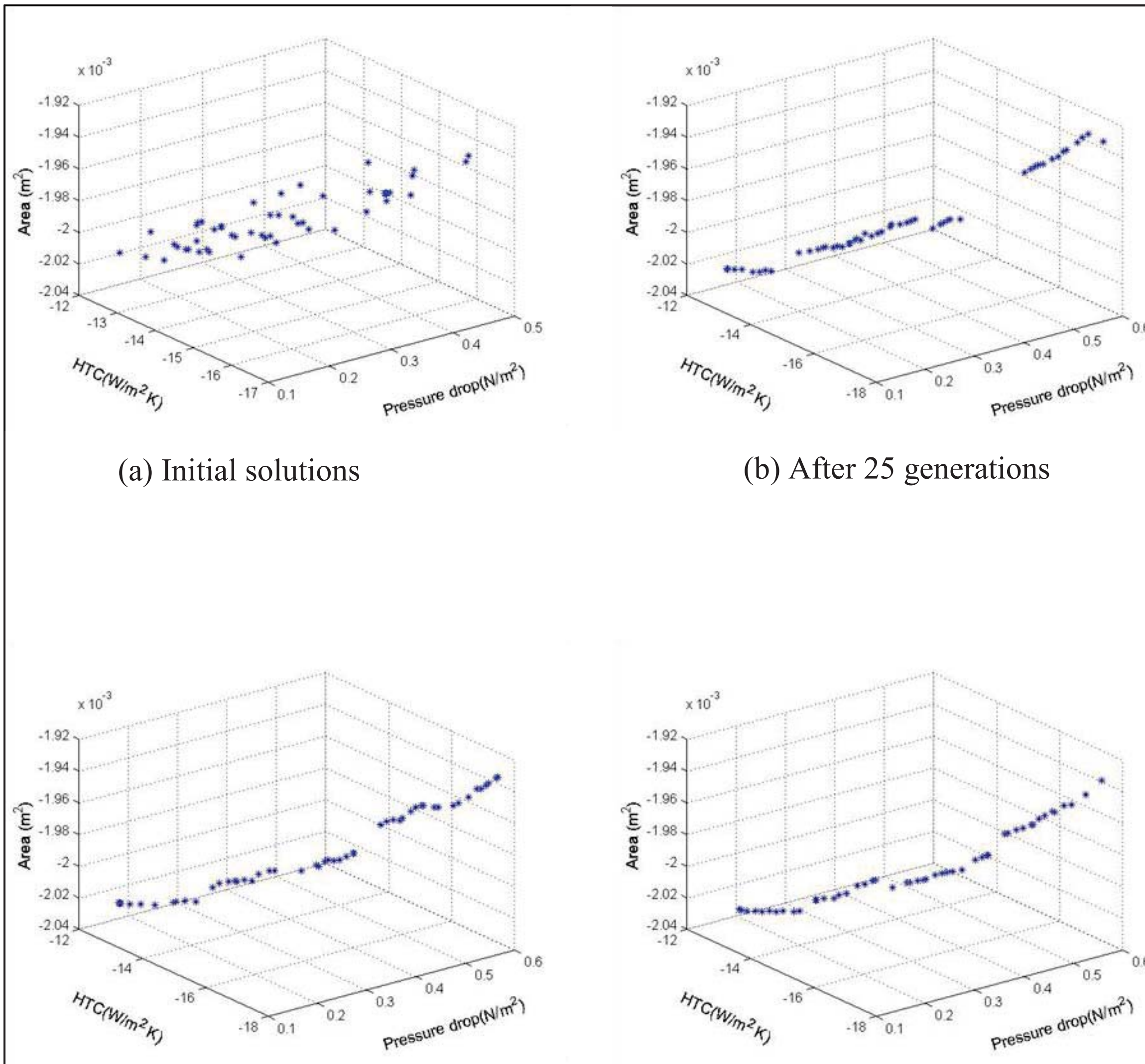
(c) After 50 generations



(d) After 100 generations

Pilot Study 17

Population size (*Pop*) = 50	Generations ($Gen_{\max}$) =100
Crossover (*c*) = 0.95 (95%)	Mutation Probability (*m*) = 0.05 (5%)



(a) Initial solutions

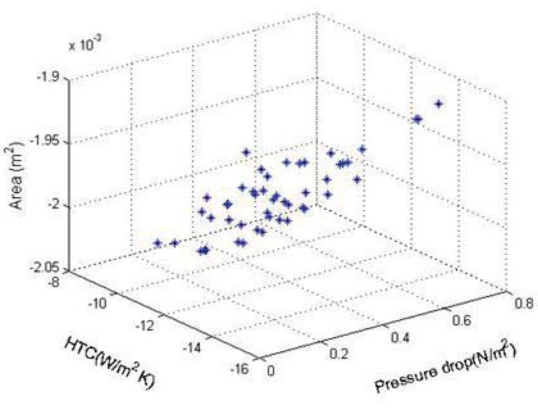
(b) After 25 generations

(c) After 50 generations

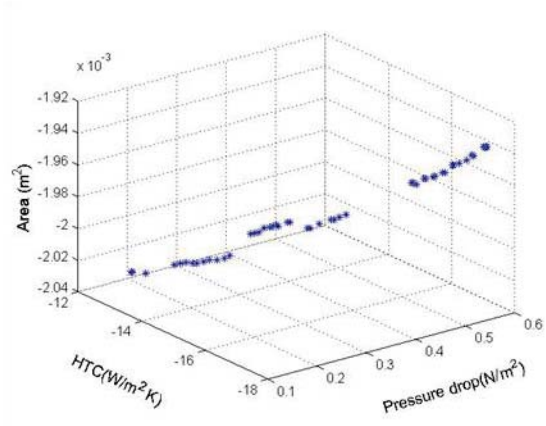
(d) After 100 generations

Pilot Study 18

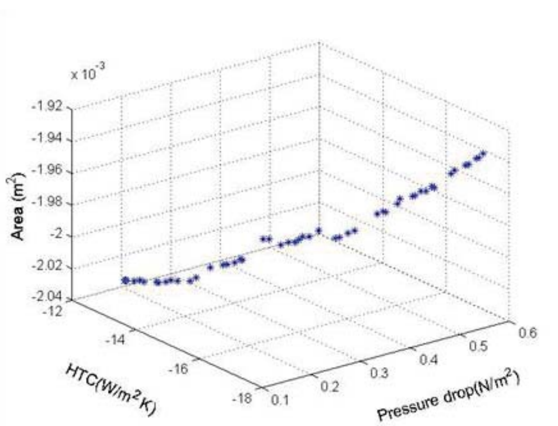
Population size (*Pop*) = 0	Generations (Gen_{max}) =100
Crossover (*c*) = 0.80 (80%)	Mutation Probability (*m*) = 0.10 (10%)



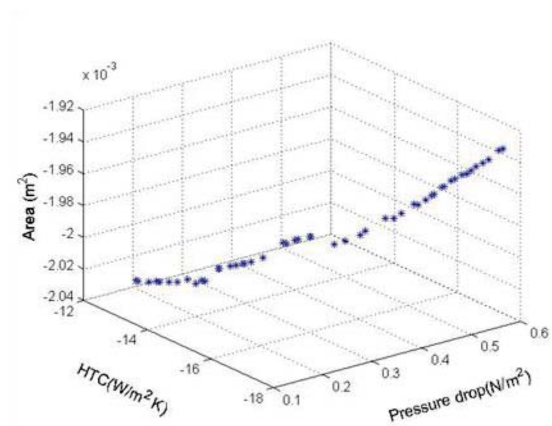
(a) Initial solutions



(b) After 25 generations



(c) After 50 generations



(d) After 100 generations

APPENDIX B: COPYRIGHT PERMISSION

Narasimha Nagaiah

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Thank you

Raju

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Narasimha Nagaiah

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Sent: Wednesday, August 15, 2012 2:09 PM
To: Narasimha Nagaiah
Subject: RE: Copyright

I apologize for missing that. You may also reprint Figure 20. The same conditions apply.

Mike

From: Narasimha Nagaiah [mailto:raju@ucf.edu]
Sent: Wednesday, August 15, 2012 1:11 PM
To: Mike Baden-Campbell
Subject: RE: Copyright

Dear Mike,

I'm sorry but I requested two of them, figure 7 and figure 20. I wrote both of them in one sentence. Can you please re send adding figure 20 also.

Again sorry for the trouble.

Regards

Raju

From: Mike Baden-Campbell [mailto:MikeB@aiaa.org]
Sent: Wednesday, August 15, 2012 1:09 PM
To: Narasimha Nagaiah
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Dear Mr. Michael Baden,

Thank you very much for fast response. Here are information regarding publication from which I will be using figures from for my PhD dissertation.

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Publication Title: Spanning The Globe With Jet Propulsion
Publication year: 1991
Publisher: American Institute of Aeronautics and Astronautics (AIAA)
Paper No: 2987
Conference: AIAA 1991 Annual Meeting and Exhibit, April 30-May 2, Arlington, Virginia

I do have copy of paper which is purchased by University (UCF), I attached the copy for your quick reference.

I hope to get permission to republish above mentioned figures in my dissertation.

Thank you very much for your help

Raju

Narasimha Nagaiah (Raju)
IEMS Dept.
University of Central Florida
Orlando, Florida-32816
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Fax: (407) 823-3299

From: Mike Baden-Campbell [mailto:MikeB@aiaa.org]
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